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Estimating Academic Attrition from Technical Training School Data: Method and Simulation Results

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14. ABSTRACT *(Maximum 200 words)*:
This study proposes a logistic regression-based approach for estimating academic attrition from technical training school data. The proposed approach enables Army personnel managers to evaluate tradeoffs when making decisions about where to set minimum enlistment standards. A large-scale simulation was conducted based on actual training school data from a selected MOS to evaluate the approach and to assess sampling error of estimated attrition rates under different sample sizes and operational scenarios. Major findings indicate that: (a) a simple approach based on the logistic regression using only cognitive aptitude information is adequate for evaluating impact of changes in minimum enlistment standards on academic attrition for MOS with medium validity or greater; (b) a large enough sample size allows smaller changes in minimum enlistment standards to achieve a targeted attrition rate with confidence; and (c) personnel and training decisions could be greatly improved by extending the current model to incorporate information in addition to cognitive aptitude. The report includes a ready-to-use statistical program for applying the proposed approach to actual training school data for the purposes of making operational decisions.

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FOREWORD

Army personnel managers and school house proponents frequently need to make tradeoffs between Soldier numbers, quality, and training to establish and defend minimum enlistment standards for entry-level military occupational specialties (MOS). The standards must be set to reconcile the difficulty of recruiting qualified individuals with the effort required for training Soldiers to perform successfully in their assigned job. When the standards are too stringent, then it will be difficult to identify a sufficient pool of qualified recruits. Conversely, if the standards are relaxed too far, then Soldiers may not perform adequately in training or in their jobs. Often, data pertaining to the tradeoffs required to establish enlistment standards exist but are not integrated into the decision process because they are not readily accessible.

This study addresses the above need by developing and evaluating a method for estimating the effects of changes in minimum enlistment standards on academic attrition rates. The proposed method can be applied to assess the practical implications of proposed changes in enlistment standards on academic attrition from technical training. Results of a large-scale simulation demonstrate the utility of the proposed method across several different operational scenarios. Recommendations and materials for applying the method, so as to ensure optimal decisions about where best to set enlistment standards for technical training, are provided in the report.

Both this study (utilizing simulation methodology) as well as other on-going ARI research (drawing on actual training performance data) were undertaken to assist managers and proponents with enlistment standards issues. The results and recommendations have been provided to the Human Resources Command staff, and deemed useful in understanding the standards setting process.

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ESTIMATING ACADEMIC ATTRITION FROM TECHNICAL TRAINING SCHOOL DATA: METHOD AND SIMULATION RESULTS

EXECUTIVE SUMMARY

Research Requirement:

Army personnel managers frequently need to make tradeoffs between Soldier numbers, quality, training effectiveness, and a host of other factors when making personnel management and training decisions. The purpose of the present study was to propose and demonstrate a logistic regression-based approach for estimating academic attrition rates. This approach enables Army personnel managers and strategic planners to evaluate the aforementioned tradeoffs when making decisions about where to set minimum enlistment standards.

Method:

This study applies a logistic regression-based framework to modeling academic attrition from technical training school data. This attrition model estimates the percentage of Soldiers meeting the minimum enlistment standards that are not expected to complete technical training for academic reasons. Data requirements of the model are simple and involve Soldier aptitude scores and training outcome data (i.e., pass or fail). The initial model estimation and subsequent attrition rate prediction analyses are packaged in a ready-to-use statistical program, making it possible for Army managers to apply the approach proposed in this study.

We conducted a large-scale simulation study to demonstrate and assess the performance of the logistic regression-based approach. Actual training school data from a selected MOS were employed to derive an initial set of realistic training performance parameters. We then alternately modified a subset of these parameters to represent different training school scenarios Army managers are likely to encounter on the job. Using known training requirements and policy in MOS schools, we repeatedly generated samples of synthetic pass/fail training outcome data from Soldier aptitude scores and training performance data simulated under the different scenarios and using different sample sizes. The logistic regression-based model was then separately applied to the replicated samples of synthetic training outcome and aptitude score data to estimate attrition rates under a range of minimum enlistment standards.

The simulation-based analysis that was carried out provided a cost-effective approach for evaluating the performance of the proposed logistic regression-based attrition model under different operational school scenarios. Equally important, the replicated simulation design enabled us to assess the sampling error associated with the attrition rate estimates under different sample sizes and scenarios. Given real-world sample size constraints, simulation provides a more reliable assessment of the unknown underlying sampling error compared to those based on statistical formulas, which typically assume very large sample sizes.

Findings:

The major findings of our simulation are threefold. First, a simple approach based on the logistic regression using only cognitive aptitude information is adequate for the purpose of

evaluating the impact of changes in minimum enlistment standards on academic attrition for MOS with medium complexity/validity or greater. Second, the sample size on which academic attrition estimates are based can significantly impact the quality of the decisions made based on these estimates. The results indicated that a sufficiently large analysis sample size allows smaller changes in minimum enlistment standards to achieve a targeted attrition with high confidence, which in turn translates to potential savings in terms of the size of the eligible applicant pool. Third, related personnel and training decisions could be greatly improved by extending the current model to incorporate information in addition to cognitive aptitude. This is particularly true for MOS where aptitude does not significantly predict performance.

Utilization of Findings:

A number of practical recommendations for performing and interpreting this analysis that could aid operational decisions are presented. In particular, the sample size analyses and simulation programs are directly useful for planning MOS training school data collection in the future. The simulation methodology used in this study is also valuable for assessing the impact of alternative training or testing requirements that may be under consideration for managing academic attrition. This study concludes with suggestions for future research that could greatly extend the proposed approach and further assist Army managers when making the personnel and training decisions that motivated this study.

ESTIMATING ACADEMIC ATTRITION FROM TECHNICAL TRAINING SCHOOL DATA: METHOD AND SIMULATION RESULTS

CONTENTS

INTRODUCTION

Background

Army personnel managers frequently need to make tradeoffs between Soldier numbers, quality, training effectiveness, and a host of other factors when making personnel management and training decisions. However, often neither the data nor methods for effectively evaluating the data are easily available to inform manager's decisions. This is problematic given the importance of the personnel decisions managers must make in an increasingly dynamic and complex operating environment, such as the Army. There are several reasons why these decisions are critical to Army managers and the Army as a whole.

First, personnel decisions ultimately determine the placement and quality of the training tens of thousands of Soldiers receive each year, which impacts future performance and morale. This is especially significant given the time and investment the Army makes in advanced individual training (AIT) of recruits, roughly $6,100 to $16,300 per enlistee (U.S. General Accounting Office, 1997), in addition to the cost of basic training. Second, these decisions are associated with major tradeoffs between one or more of the Army's operational objectives. For example, while raising minimum enlistment standards is likely to produce higher levels of (overall) Soldier performance, doing so makes it substantially more difficult to meet accession goals, as more Soldiers would fail the standards. Likewise, while lowering enlistment standards makes it easier to fulfill accession goals, overall training quality and subsequent performance may suffer, as the average quality of students would be lower. Further, the tradeoffs associated with these decisions are often complicated by shifts in the Army's recruiting environment or public policy, over which Army personnel managers exert little control.

In summary, understanding the impact of changes in minimum enlistment standards on training attrition (and other personnel outcomes) is important for: (a) maintaining (or improving) overall Soldier performance and morale; (b) effectively managing Army jobs or military occupational specialties (MOS) and the larger recruiting and training mission; and (c) identifying the best solution for resolving the critical tradeoffs managers face when making key personnel decisions.

Purpose of Report

This report serves the following purposes:

1. To propose and describe an approach for estimating academic attrition rates under different operational scenarios. Note that this report deals exclusively with modeling *academic* attrition. Training attrition due to *non-academic* reasons (e.g., health) is not addressed by the approach proposed and described in this report.

2. To discuss the effects of lowering (or raising) minimum enlistment standards on academic attrition rates estimated using the proposed approach. Note that "minimum enlistment standards" and "cut scores" are used interchangeably throughout this report. For those unfamiliar with the terminology, "cut scores" are defined as the minimum score a Soldier can achieve on a screening test (or other assessment) to be eligible for technical training in a

particular MOS. In particular, we discuss issues (e.g., practical, methodological, and statistical) related to interpreting the effects of raising (lowering) cut scores.

3. To provide practical recommendations for conducting an attrition rate analysis using the proposed approach. Specifically, we present recommendations regarding: (a) collecting data for analysis; (b) specifying and estimating the model; and (c) inferring the effects of changes in enlistment standards on academic attrition.

METHOD

This study applied a logistic regression-based approach to modeling academic attrition. Using a simulation-based analysis strategy based on real-world data, we estimated attrition rates under different operational conditions Army personnel managers are likely to encounter. As an overview, this section is organized as follows. First, we describe and propose a logistic regression-based model for estimating academic attrition. Additionally, we consider its advantages and disadvantages relative to a model predicting individual test scores (or a composite of these scores). Second, we describe data quality issues and practical constraints encountered with existing Army data. These issues provide the basis for the current study's implementation of a simulation-based approach for investigating the effects of changes in Army enlistment standards on academic attrition. Third, we describe the simulation-based approach employed in this study. Specifically, we discuss its advantages and detail the procedures used for estimating key parameters and attrition rates. Additionally, we describe the selection of factors used to represent the different operational scenarios Army managers are likely to encounter when making decisions about enlistment standards and academic attrition rates. A mathematical description of the structure of training school data used in the simulations is provided in Appendix A. Tables and charts summarizing the results of the simulation are presented in Appendices B and C. Accompanying Statistical Analysis System (SAS) code for replicating our simulation and applying the proposed logistic regression-based model operationally to training school data can be found in Appendices D and E.

Modeling Approach

The analysis of the impact of changes in minimum enlistment standards (i.e., cut scores) on academic attrition, viewed simply, involves the ratio of the number of applicants who are not expected to successfully complete the training to the total number in the relevant applicant pool that are eligible for the target MOS. Since cut scores are based on aptitude area (AA)[1] scores that are positively correlated to training (and job) performance, raising the cut score is expected to leave fewer but higher quality eligible applicants. This is expected to yield a lower training

[1] Aptitude area (AA) composite scores are estimates of future success in entry-level training and job performance in an MOS. AA scores are used operationally by the Army to assign recruits to an MOS. AA composites and the Armed Forces Vocational Aptitude Battery (ASVAB) subtests which comprise them are described in many sources (Greenston, 2002; Diaz et al., 2004).

attrition rate because applicants who continue to meet the new cut score are more likely to successfully complete the training compared to applicants who no longer meet the new cut score and are dropped from the eligible pool.

Mathematically, there are two key components in evaluating the impact of changes in cut scores on academic attrition rates. The first component is a model describing the relationship between the AA score of an applicant and the probability that he or she will not successfully complete the training. The second component is the density or distribution of the number of applicants at various levels of AA scores in the relevant applicant pool. These ideas are represented in the equation below, which describes the attrition rate A(C) for the eligible applicant pool as function of the cut score C.

$$A(C) = \frac{\int_{C}^{\infty} P(x) f(x) dx}{\int_{C}^{\infty} f(x) dx}$$

The first component, represented by the function P(X), and the second component, represented by the density f(X), together determine the numerator, which corresponds to the count of applicants that are expected to not successfully complete the training for a given cut score. The denominator, which corresponds to the total number of eligible applicants, is determined entirely by the density f(X) for a given cut score. This equation can be interpreted as the average of the probability of attrition weighted by the density of the AA scores that are above the minimum cut score C. The density f(X) representing the applicant pool and P(X) are described in the next two sections.

Applicant Pool Density

The two natural choices for the applicant pool that are relevant to the analysis of the relationship between cut score and training attrition are the youth population and the Army accession (or input) population. Technically, the choice of reference population matters as the shape of the density f(X) determines the underlying weights employed in the computation of the attrition rate. For practical purposes, however, it does not appear that the choice between these two reference populations substantially impacts the overall attrition rates on the range of cut scores that are likely of interest to Army managers. The rationale for this is as follows.

The Army accession distribution is truncated on the lower end and, to lesser extent, on the upper end relative to the youth population distribution. The form of the attrition formula A(C) above, however, ignores the part of the distribution to the left of the cut score C. Cut scores that are operationally important are expected to be within one standard deviation of the youth population average (see following section for a discussion of cut score range). Practically, this means that the left end of the distribution where the youth population and Army accession distributions differ is ignored in the computation of the attrition rates. This is not the case with the upper end, which is included in the computation of attrition rates. However, differences in the upper range of the youth and Army accession populations are not expected to adversely impact computed attrition rates because these differences are not as large as those in the lower

range. Additionally, this is the part of the distribution where the density f(X) is small, and hence, does not carry significant weight in the computation of the attrition. In summary, differences in the youth and Army accession populations will not affect attrition rate computations to a meaningful extent.

Because of the small impact of differences between the youth and Army accession populations on the expected attrition rate, the choice between them is best guided by practical considerations. For example, changes in the Army's recruiting environment could make the truncation on the high end of the youth population more substantial than typically observed. This would be the case when the economy is strong and the job market easily absorbs greater numbers of high quality youth. In this case, an Army accession reference population might be tailored using data from previous recruiting years that would be representative of a strong job market. Using this particular reference population, one would obtain slightly higher attrition rates, as high quality recruits would be less represented (i.e., carry less weight) in the computation of training attrition. Therefore, there may be cases where one population is preferable because modeling that specific population produces estimates of attrition that more strongly reflect the current operational environment in which decisions about where to set enlistment standards will be made.

In our approach, we use a youth population-based normal distribution for f(X) in the simulation for convenience and because there was not a particular operational environment of special interest. The approach and computer program for estimating attrition rates operationally (see Appendix D) can easily be adapted using any reference population.[2]

Probability of Training Attrition

The second component in the computation of A(C) is a function P(X) describing the relationship between training attrition rate and AA score of an applicant. The function P(X) is the probability that an applicant with AA score equal to X will not successfully complete training. That is, P(X) evaluates to a value between zero and one that represents the percentage of individuals with AA score X that are expected to academically attrit.

Note that in our overall framework, the complete "cut score attrition model" is A(C) and not P(X). The latter is the conditional probability of attrition given the applicant's AA score. On the other hand, the cut score attrition rate A(C) averages the conditional probabilities P(X) evaluated in the AA score range above the cut score C, using the appropriate applicant pool density f(X) as weights. The function A(C) evaluates to the probability that applicants with AA score *equal to or better* than C will not successfully complete training.

[2] The averaging used in the computation of attrition in the SAS program is based on applicant pool quantiles rather than a numerical integration based on the specific form of f(X), for example. The quantile-based approach is flexible as these may be computed from a large enough data base representing the "target" applicant pool; the exact form of f(X) need not be known.

Training Outcome Variable

The exact form of P(X) is dependent on the type of "outcome" variable used in modeling attrition. The traditional outcome variable used in this type of analysis is the simple "dummy" or binary variable taking the value "1" to indicate that the applicant did not complete training or "0" to indicate that the applicant completed training. In the MOS school data that we used in this study, this dummy variable was constructed from a "student output" code that indicates whether or not the student graduated from training. There is also a "reason" code in the data that can be used to classify non-completion into academic or non-academic attrition. Students that were classified as non-academic attritions were excluded from our analysis data.

In this study, we also learned about the structure of MOS school training requirements and testing process that are relevant in determining applicant passing or failing. A more detailed technical description of the process is provided in Appendix A. Generally, students take a series of tests that can be characterized as a multiple hurdle system. The scores on the tests that a student took represent a multivariate outcome variable that provides more detailed information relevant to attrition analysis. This multivariate outcome vector of test scores and the knowledge of the underlying attrition "generation mechanism" is useful in defining a form of P(X) that is directly related to the underlying process. However, it is a more involved approach using a multivariate type of analysis that we believe is not suitable for routine calculations. The amount and costs in terms of data quality requirements in a multivariate test scores-based approach are also far greater than the binary attrition variable approach.

The approach to modeling P(X) employed in this study is based on the binary or dummy pass/fail outcome variable. However, for the simulation experiments that were carried out, we generated the pass/fail outcome observations using a test score-based pass/fail mechanism implementing known school testing policy relevant to training attrition.

Logistic Regression Model of Attrition

We used the logistic regression of the pass/fail outcome observation on applicant AA score to specify P(X). Formally, the relationship between applicant attrition probability and AA score that is equal to X is

$$P(X) = \frac{\exp(a + bX)}{1 + \exp(a + bX)}$$

which is parameterized by some unknown constants a and b. The function P(X) is defined between zero and one and is inversely related to the AA score. The value of P(X) decreases to zero as AA score increases and it increases to one as AA score decreases.

There are several advantages to a logistic regression-based approach. First, logistic regression permits the modeling of nonlinear relationships between relevant predictor variables and the dependent variable of interest (Cohen, Cohen, West, & Aiken, 2003; Tabachnick & Fidell, 1996). From an operational perspective, it is not unreasonable to expect that many of the predictors of academic attrition (e.g., cognitive aptitude, education, disciplinary problems, etc.) are nonlinearly related to attrition. For example, for those high in cognitive aptitude the

relationship between aptitude and attrition is likely to be flat as few high aptitude individuals fail to complete training and the expected probability for success is uniformly high. Conversely, for those low or average in cognitive aptitude the relationship is likely to be positive, particularly for those in the middle range of aptitude, as there is greater variability in the proportion of Soldiers failing to complete training and the probability of success varies measurably with level of cognitive aptitude (e.g., the higher one's standing on cognitive aptitude, the higher his/her probability of successfully completing training).

An additional advantage to modeling potential nonlinear relationships is that a logistic regression approach will do a better job of predicting academic attrition across the full range of cognitive aptitude, including those in the extremes (e.g., low or high in cognitive aptitude), compared to a linear probability model (LPM) obtained using ordinary least squares (OLS) regression. This is especially important since operationally, it is those individuals in the extremes, either the low or high end of cognitive aptitude, who will exhibit the greatest probability of attriting or not attriting, respectively. Under LPM, predictive accuracy is weakest for cases in the extremes (Cohen et al., 2003; Guion, 1998; Tabachnick & Fidell, 1996), precisely the cases the Army is most interested in. Therefore, the ability to model nonlinear relationships is important *both* for understanding the nature of the relationship between Soldier characteristics (e.g., cognitive aptitude, education, etc.) and academic attrition, and more operationally, for accurately predicting and estimating attrition rates.

When compared to a multivariate test scores-based approach to modeling P(X), an advantage to the logistic regression approach is that it simplifies interpretation by aggregating multiple test scores into a single, meaningful outcome variable of interest, academic attrition. From an operational perspective, the Army is ultimately interested in predicting and explaining attrition, not necessarily trainee performance on specific test(s), which vary from school to school. Having a single, overall outcome variable, as opposed to ten or more different variables, facilitates the analysis. Importantly, it increases the ease with which Army personnel managers can successfully implement any proposed methodology for assessing changes in enlistment standards on attrition rates in the field.

In summary, the advantages of a logistic regression approach recommend it over a model focused on individual test scores. Because of the model's advantages, and its fit with the Army's operational goals, it is the preferred approach for modeling academic attrition. An alternative to the logistic model for specifying P(X) is the probit model. These two models, however, are practically equivalent.

Issues Related to Modeling Attrition

We have identified three potential issues related to our modeling of P(X). We describe each of these in turn.

Criterion Contamination. The strongest advantage of the logistic model approach (or equivalent binary model) is its simplification of the underlying attrition-generation process, in this case involving at least 10 to as many as 30 test scores, into a single, binary outcome variable indicating pass/fail. This simplification of the underlying relevant outcome, however, has its pitfalls. Specifically, in working with the "student output" variable in our data, we came across

cases where a student was classified as "graduate" (i.e., not attriting) but the test scores indicated that he or she failed at least one test twice. Technically, failing a test twice means that a person cannot complete training. We were informed that this type of "exemption," which is a form of criterion contamination, is in fact possible. For the purpose of this analysis, which is concerned specifically with academic attrition, an applicant was classified as an attrition if he or she did not pass a test after two attempts. Because "exemptions" failed a test twice, these cases were classified as attritions. This was done for two reasons.

First, we did this to be consistent with official school policy. Officially, school sponsors and Army personnel managers define academic attritions as those recruits who do not successfully pass all tests required for technical training. According to school policy, recruits are permitted a maximum of two attempts to pass a required test. Should a recruit fail to pass a test on the second attempt, he or she technically cannot complete training without some form of remedial action. Therefore, the practice of classifying "exemptions" as attritions is consistent with official school policy and, more practically, will yield the most accurate assessments of the effects of changing enlistment standards on academic attritions. That is, while estimates may be higher than actual attrition rates, owing to the fact that "exemptions" were excluded during the estimation process, the estimates produced will more accurately reflect the actual relationship between enlistment standards and attrition. Classifying "exemptions" as not attriting, or excluding them from the analysis entirely, would produce inaccurate estimates of the effects of changing enlistment standards because doing so changes the underlying enlistment standards-attrition relationship. Put simply, classifying "exemptions" as attritions removes "noise" that would otherwise cloud the actual connection between enlistment standards and academic attrition. It is that actual connection which guides and informs official school policy and personnel decision-making.

The second reason for classifying "exemptions" as attritions, not unrelated to the first, is that there is likely to be insufficient data to model "exemptions." Specifically, the reasons for an exemption are not recorded or easily accessible from technical training data. In addition, "exemptions" are not expected to be meaningfully related to enlistment standards or other variables (e.g., demographics) readily available to school sponsors and Army personnel managers running an attrition rates analysis. More importantly, the reasons for an "exemption" are not likely to be systematic, but random; varying between-recruits, between-classes, and probably both (e.g., between-recruits within the same class), in non-systematic ways. Taken together, this means that "exemptions" cannot be alternatively classified (or modeled) in reliable ways other than as "attritions" without introducing some amount of bias into the estimation process. If interested, Army school proponents and personnel managers may adjust estimated attrition rates after the fact to take into account expected exemptions. However, we would generally advise against this practice, as meaningful data for making such adjustments is not likely to be easily accessible.

Incidental Truncation. A second potential issue related to modeling P(X) is incidental truncation. This typically occurs in non-experimental studies (i.e., using non-randomized samples) where the underlying selection mechanism is not random with respect to the outcome variable. It can be an issue in modeling P(X) as factors influencing a student's assignment (selection) into an MOS, such as education, other demographics, or incentives, can be associated with academic attrition. For example, a student with at least high school diploma might have an

easier time adapting to the formal training environment in an MOS school. In the case of enlistment bonus incentive, which is typically tied to a recruit's completion of the term of service, a student who contracted to receive a high bonus might have an extra motivation to successfully complete the training. This hypothesis is significant as the bonus amount varies across MOS and is designed to partly influence an applicant's selection of MOS in a way consistent with Army priority.

Note that the use of an AA cut score to determine eligibility is not a reason for incidental truncation in our problem as the model P(X) is already conditional on the AA score (X). Note also that in this issue we are concerned with the association between factors influencing assignment into an MOS versus the likelihood of attrition that is *unexplained* by the AA score (i.e., the "residual" attrition conditional on X). In particular, the more a factor is highly correlated with the AA score the less likely it is to contribute to incidental truncation.

Formally, incidental truncation is generally handled by incorporating the selection process in the modeling of the outcome variable. For example, in the linear regression model case with continuous outcome variable, a two-step estimation procedure (Heckman, 1979) is commonly carried out to handle incidental truncation. In the first step, a probit model representing the selection process is estimated, while the second step carries out the least-squares estimation for the substantive model that incorporates a selection component (see also Greene, 1997, pp. 975-978). This approach or an alternative maximum likelihood method involves jointly modeling a binary variable indicating selection and a continuous outcome variable that is essentially censored for individuals that are not selected. Note that the "full sample" used for carrying out the estimation in this method includes individuals excluded from the selection sample (i.e., entire sample before selection).

In our problem, the potential incidental truncation issue is similar except that we are also dealing with a binary outcome variable that is observed only for individuals that are selected into the MOS. In this context, the estimation of P(X) can be carried out using a "censored bivariate probit" model (Boyes, Hoffman, & Low, 1989) in which the binary outcome variable representing attrition is censored if the selection binary variable equals 0 (i.e., not selected into the MOS). Using this estimation framework requires switching from the logit to the probit model for P(X).[3] More importantly, however, the full sample required for carrying out estimation of P(X) that incorporates incidental truncation includes students not selected into the MOS under consideration. This full analysis sample can be Army accessions corresponding to the fiscal years represented by students in the MOS school. These data were not available in this study. Boyes et al. (1989) provide the maximum likelihood equations necessary for carrying out the estimation.

Mixture of Old and New AA Scores. A third potential issue in the implementation of the proposed method is the mixture of old AA scores based on nine ASVAB subtests (prior to FY 2002) and new AA scores based on seven ASVAB subtests. Although this may be less of an issue for MOS with large numbers of trainees, particularly as the Army moves past FY 2002, there are still likely to be cases where combining school data using old and new AA scores to

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[3] An analog to the bivariate probit is the bivariate logistic model (McCullagh & Nelder, 1983), where both the outcome and selection indicator variables are marginally represented by separate logistic model.

achieve a desired sample size is necessary. Likewise, this conversion is definitely recommended if one is estimating rates from historical data for purposes of establishing baseline(s) by which to compare expected rates. For handling this issue we propose converting the old AA scores into the equivalent new AA scores. The new AA score should then be employed in the remainder of the analysis (e.g., for both P(X) and A(C) equations). Note that conversion of the old AA scores is only an issue if the original scores on nine ASVAB subtests are no longer available. The procedure for converting old AA to new AA scores is documented in Appendix A. For purposes of evaluating the proposed method, no conversions were necessary.

Data Collection

The Army Training Support Center (ATSC) at Ft. Eustis, VA provided ARI with training school data for building and testing a model of academic attrition. Data for four MOS roughly covering the last two fiscal years were extracted from ATSC'S Automated Instructional Management System (AIMS) database. The MOS selected and for which training performance data were available represent a variety of jobs found in the Army. The dataset for each MOS consisted of data from multiple classes.

For the purposes of the present study, a simulation-based analysis strategy was adopted. In brief, this strategy uses actual MOS data to produce computer-generated or synthetic samples that serve as input to the estimation of attrition rates and the analysis of changes in these rates from adjustments in enlistment standards. It should be emphasized that simulations are *not* intended to be a substitute for real-world data. Operational decisions are best based on the analysis of real-world data. However, a simulation was preferable for purposes of testing and evaluating the proposed method, which was the primary goal of the current study, for the following reasons.

First, as the primary goal of the current study is to propose and evaluate a method for estimating academic attrition rates, a simulation-based analysis strategy is preferred. Since the proposed method is intended for operational use, it is critical that the performance of the method be evaluated as comprehensively and accurately as possible. A simulation-based approach best meets these requirements. By taking a simulation-based approach, we could ensure that the results from evaluating the proposed method were not dependent on idiosyncrasies present in the available data. This enabled us to evaluate the performance of the proposed method as accurately as possible. For example, across three of the four MOS, the available sample size was generally small. Small sample size is problematic, as it is associated with higher levels of sampling error, which adversely affects the accuracy and precision of estimates (Cohen et al., 2003; Hunter & Schmidt, 1990). Because of this, using the available data was likely to produce inaccurate and potentially biased estimates, thereby making it difficult to accurately evaluate the proposed method.

Second, and more importantly, by using the available data, we would be unable to assess the impact of sampling error on estimates produced by the proposed method, information that would be extremely useful when applying the method in the field. A simulation-based approach would be advantageous in this regard, because it would permit us to model the adverse effects of sampling error on the accuracy of attrition rates computed operationally. With this information we could provide guidance on how best to interpret these estimates when making actual

decisions. For example, with this information, we could offer recommendations regarding *when* to make adjustments to enlistment standards and the *magnitude* of the adjustment needed to achieve a desired level of attrition. While there are computational formulas for estimating sampling error, these formulas typically assume very large sample sizes, sample sizes greater than those of the available MOS. Therefore, a simulation-based approach would provide the most effective means for assessing the impact of sampling error on attrition rates estimated under the proposed method, and its implications for decision-making.

From an operational perspective, a simulation-based approach would be advantageous for two additional reasons. First, a simulation-based approach would permit the estimation of attrition rates under different operational scenarios; estimates that would be impossible to model given that the existing data were not collected with these particular scenarios in mind. Second, when done right and in operational environments like the Army's, simulations provide a cost-effective means for studying different combinations of variables that might otherwise take multiple, individual studies (and a large amount of Army resources) to compile. Conducting simulations saves valuable time and critical operational resources. More importantly, the information collected from simulations can greatly optimize the design of follow-up studies using real-world data. By identifying the variables most relevant to the outcome(s) of interest, researchers can best maximize the gains, while minimizing the costs, of future research efforts.

Simulation-Based Analysis Strategy

Overview and General Description

To assess the proposed approach for evaluating changes in minimum enlistment standards on academic attrition, we employed a simulation-based analysis strategy that involved the following three major steps.

1. To ensure that our findings would approximate results from real-world data, we selected an actual MOS whose empirically estimated parameters would serve as input for constructing the computer-generated samples for use in the simulation. In selecting the MOS, care was taken to identify the MOS: (a) whose data would provide the most accurate estimates; and (b) whose estimated attrition rate was comparable to the attrition rate typically observed in the Army (e.g., between 10% and 20%). After identifying the MOS that best met these criteria, we computed the relevant parameters from which the computer-generated samples would be based.

2. Based on these real-world parameters, we generated synthetic samples of varying sample sizes (N) that approximated relevant properties of the different MOS found in the Army. Each sample consisted of synthetic AA composite and training performance data for N trainees. To simulate samples that reflected the different operational scenarios Army personnel managers were likely to encounter in the field, we varied the parameters from which the synthetic samples were generated. Technical notes on how AA composite and training performance data were simulated can be found in Appendix A. From the synthetic training performance data, we

computed a dichotomous attrition variable indicating if a trainee did or did not pass training.[4]

3. Using the synthetic samples generated in Step 2, we estimated academic attrition rates (and their corresponding standard errors) associated with varying cut scores. These estimates were based on regression parameters obtained by applying the logistic regression-based model to the synthetic AA composite-attrition data (produced in Step 2), and aggregating estimates across samples representing the same *N* and operational scenario. From this, we were able to infer the effects of changing enlistment standards on academic attrition under the different operational scenarios Army personnel managers were likely to encounter on the job.

Simulations based on real-world parameters, such as the approach employed in the current study, have been widely used in Army research and other social sciences, such as applied psychology, economics, and public policy. For example, comparable simulation-based approaches have been successfully used to identify strategies for maximizing the efficiency of Army classification (e.g., Johnson, Zeidner, & Leaman, 1992; Scholarios, Johnson, & Zeidner, 1994; Statman, 1993; Zeidner, Johnson, Vladimirsky, & Weldon, 2000) and within applied psychology, to identify combinations of different predictors that maximize both job (or training) performance and demographic representation (e.g., Bobko, Roth, & Potosky, 1999; Sackett & Roth, 1996; Schmitt, Rogers, Chan, Sheppard, & Jennings, 1997). While simulations, including that of the current study, are not intended to be substitutes for real-world data, as mentioned in the previous section they do offer advantages, particularly when evaluating an estimation method.

This section is organized as follows. First, we detail the selection of the MOS used for producing the computer-generated samples for the simulation, and the procedure for obtaining the real-world parameters on which these samples were based. Second, we discuss the construction of the different operational scenarios under which attrition rates would be estimated and the procedure for generating the synthetic samples for use in estimating academic attrition. Third, we describe the procedure for estimating academic attrition rates (and accompanying standard errors) under varying cut scores across the different operational scenarios. SAS programs, and accompanying technical documentation, for replicating the simulation are available in Appendix D.

Selection of MOS and Procedure for Estimating Parameters for Computer-Generated Samples

Selecting an MOS. Although a simulation-based analytic strategy was selected, steps were taken to ensure that findings from our simulation approximated those of the real-world. To do this, a single MOS was selected to provide the parameters on which the computer-generated samples would be based. The MOS selected was meant to reflect the typical MOS.

While multiple MOS were available and could have been aggregated to form the typical (or average) MOS, we did not follow this approach for two reasons. First, different MOS use

[4] Attrition was *not* simulated directly, but based on simulated performance across a battery of training tests. Details on how this was done appear later in the Method section.

different AA composites to determine eligibility and require a different number of tests to complete training with different passing grades, which makes simple aggregation difficult. Second, the sample of MOS available was small (4) and generally reflected a convenience sample. Therefore, the available MOS may not have been representative of the full population of Army jobs, making it unlikely that aggregating across MOS would have produced the typical MOS.

When selecting the MOS to serve as input for constructing the computer-generated samples, care was taken to identify the MOS from those available: (a) with the fewest data quality issues (e.g., data entry errors); and (b) whose estimated academic attrition rate was comparable to that typically found in the Army (between 10% and 20%). Extensive diagnostic and screening procedures were conducted on all MOS. After reviewing the available MOS, we identified 55D (Explosive Ordnance Disposal) which best met these criteria and, thereby, was chosen for estimating the real-world parameters on which the computer-generated samples would be based. Specifically, this particular MOS was selected because: (a) there were a reasonable number of cases with complete training performance data; (b) its cases exhibited the least criterion contamination; and (c) its observed attrition rate, taking into account retests, best approximated that of the typical MOS.

Procedure for estimating parameters. Before constructing the computer-generated samples, we selected and estimated the parameters on which these samples would be based. The following parameters were selected: (a) mean, variance, and distribution of AA composites; (b) mean, variance, and distribution of test scores (e.g., training performance); (c) AA composite-training performance validities; (d) error correlation matrix of the test scores; and (e) regression parameters (e.g., intercept and slope) from regressing test scores onto AA composite scores. As a brief overview, the following steps were taken in estimating the parameters on which the computer-generated samples would be based:

1. The dataset for the selected MOS was cleaned and prepared for analysis.

2. Relevant parameters were computed empirically using the cleaned dataset.

3. Our procedure (and accompanying SAS program) for generating synthetic training performance data was verified. Specifically, we checked that the parameters (listed above) of the synthetic samples approximated those of the selected MOS.

Each of these steps is detailed below.

First, after the MOS was selected, the dataset containing data for that MOS was prepared for analysis. The available data were cleaned and the integrity checked. More specifically, in preparing the dataset we: (a) merged multiple records for a single participant into a single record; (b) screened data for coding errors, such as checking to ensure that the minimum and maximum values for test scores, AA composite scores, and other relevant variables were within the legitimate range; and c) deleted problem cases (e.g., participants having AA composite scores below the operational cut score) from the dataset, so as not to bias empirically estimated parameters.

Second, using the dataset cleaned in the preceding step, key parameters were computed empirically from the available data. Key parameters computed included: (a) mean and variance of AA composite scores[5]; (b) mean and variance of test scores (e.g., training performance); (c) AA composite-training performance validities; (d) error correlation matrix of the test scores; and (e) regression parameters (e.g., intercept and slope) from regressing test scores onto AA composite scores[6]. These parameters became the real-world data from which the computer-generated samples would be constructed. This is important, as one of our goals was to simulate computer-generated samples whose properties (e.g., training performance) would approximate those of operational MOS as closely as possible. Only data on cognitive aptitude (as reflected in AA composite score) were incorporated into the model. Therefore, properties (e.g., demographics) other than cognitive aptitude are not (directly) reflected in the synthetic samples. This procedure was followed because the focus of the current study is on changes in enlistment standards, and cognitive aptitude is directly tied to the setting and application of those standards.

For the third (and final) step, after computing relevant parameters empirically for the selected MOS, we checked the integrity of the procedure (and accompanying SAS program) for generating the samples of synthetic data. Specifically, we verified that the parameters (listed above) estimated empirically from the selected MOS would approximate the same parameters obtained from pilot samples of synthetic data. Technical details related to our simulation procedure are documented in Appendix D. In brief, the procedure is regression-based using empirically derived intercepts and weights. These regression parameters were then used to simulate samples of synthetic data that closely reflect the properties of the selected MOS (e.g., AA composite-test score validities) on which the samples are based.

To verify the integrity of the procedure and accompanying SAS program for producing the computer-generated samples, we conducted a series of pilot simulations. For the pilot simulations, we constructed four synthetic samples (N=10,000) based on the real-world parameters computed for the selected MOS. Each sample contained synthetic AA composite and training performance data for an MOS school. For each synthetic sample, we compared: (a) the simulated AA composite scores to real-world AA scores; and (b) the properties of the simulated training performance data to those of the real-world performance data.

First, to verify the simulated AA composite scores, we computed the mean and variance of these scores and compared them to those of real-world AA scores. Additionally, we checked

[5] Since only a single AA composite is used operationally to set minimum enlistment standards for most MOS, data (e.g., mean, SD, and AA composite-training performance validities) for a single AA composite, specifically the composite most relevant to the MOS in question, were computed.

[6] Based on the data available, recruits were required to pass 17 tests to complete technical training for MOS 55D. The following are the observed regression parameters (in parentheses--constants first, unstandardized regression weights second) for each of these 17 tests: Test1 (63.56, .24); Test2 (86.83, .06); Test3 (62.56, .24); Test4 (82.93, .10); Test5 (74.32, .18); Test6 (80.10, .11); Test7 (75.46, .11); Test8 (39.49, .43); Test9 (68.84, .17); Test10 (63.04, .23); Test11 (60.04, .25); Test12 (68.74, .18); Test13 (85.61, .02); Test14 (69.99, .22); Test15 (62.45, .24); Test16 (86.41, .03); Test17 (79.77, .13). Note, these and other key parameters computed from the MOS 55D sample, which became the basic input to the simulation, can be found in Appendix D.

the distribution (divided into quartiles) of simulated AA scores to that of the real-world scores. *Both* within each sample and averaged across all four samples, the mean, variance, and distribution of synthetic AA composite scores closely matched that of the real-world AA composite data.

Second, to verify the simulated training performance data, we did the following. Using the synthetic samples, we computed the mean, variance, and distribution of training performance (or test) scores and compared these descriptives to those of the real-world parameters. Both within each sample and across all samples, the mean, variance, and distribution of synthetic test scores closely approximated their corresponding real-world parameters. Next, we calculated the AA composite-training performance validities. As with the basic descriptives, validities estimated for the synthetic samples were comparable to real-world validities, across all training tests. We then estimated the error correlation matrix[7] for the training performance tests (i.e., correlations among the residuals for the different tests). Consistent with other parameters, the error correlation matrix of the synthetic samples matched the matrix used to simulate the synthetic data. Finally, we regressed simulated training performance scores onto AA composite scores (for each of the tests required to complete training for the selected MOS). We then compared the regression parameters (i.e., intercepts and regression weights) computed for the synthetic samples to those estimated using the real-world data. Within each sample and across all samples, the regression parameters obtained for the synthetic samples were comparable to the corresponding real-world parameters, across the full battery of training tests.

As an additional pilot, we varied key parameters (e.g., mean and variance of AA composite scores) to see if these changes would be reflected in subsequent synthetic samples. Multiple synthetic samples (*N*=10,000) were generated based on these modifications. Results from this additional pilot further verified the integrity of the procedure and accompanying SAS program, as changes in selected parameters were accurately reflected in the updated synthetic samples.

In summary, both the procedure and program for generating synthetic samples for use in the simulation were satisfactorily verified. Taken together, the findings from the pilot showed that our procedure successfully replicated and approximated real-world data, producing samples that closely reflected the properties of an actual MOS.

Selection of Operational Scenarios for Assessing Effects of Changes in Enlistment Standards on Attrition Rates

To place the effects of changing enlistment standards on attrition rates in context, we sought to identify operational scenarios Army personnel managers are likely to encounter on the

[7] Note, the error correlation matrix computed empirically for the real-world MOS contained negatively correlated residuals. Prior to running the full simulation, we compared results from our pilot modeling negatively correlated residuals versus *not* modeling negatively correlated residuals, and there were no substantial differences in the estimates produced. Therefore, to simplify the simulation, and because we did not have sufficient data to fully investigate these issues, negatively correlated residuals and residuals close to zero were set to zero for purposes of generating the synthetic data used for our simulation.

job. Doing so would assist Army managers in understanding the implications of changes in enlistment standards on academic attrition across a variety of different operational environments. To this end, we identified factors (and levels to these factors) that would meaningfully impact the interpretations Army managers make about proposed changes in enlistment standards and attrition rates. The specific factors included and the rationale for including each are described below.

School sample size. Operationally, MOS differ in size; some MOS are larger than others. Therefore, the number of Soldiers receiving training for a particular MOS will also vary. When making decisions about raising (or lowering) enlistment standards, the school sample size (N) on which attrition rates are based will meaningfully impact these decisions. When attrition rates are based on school sample sizes that are small (e.g., $N \leq 100$), the error associated with these estimates will be larger. Practically, this means the "true" attrition rate could vary considerably, and may be quite different than the rate observed. For example, while the observed rate may be 15%, due to error the "true" attrition rate could actually be anywhere from 9% to 21%. Because of this, Army personnel managers need to be careful when deciding whether to change current enlistment standards and how *big* of a change is necessary to achieve operational objectives. To illustrate the potential impact of error (associated with school size) on attrition rate estimates and the decisions based on these estimates, we varied school sample size (N=100, 200, 400, 800, 1600, 3200) when estimating academic attrition. The sample sizes selected represented levels at which we expect substantial, and practically meaningful, differences in the amount of error associated with estimated attrition rates.

Range of minimum enlistment standards or cut scores. Because of differences in the criticality of the job or accession goals, minimum enlistment standards will vary across MOS. In general, as enlistment standards are raised (lowered), attrition rates are expected to decline (increase). The attrition rates may also vary with enlistment standards, such that the rate by which attrition decreases will be steeper when standards are in the low to medium range, but gradually flattens out when standards are high. Attrition rates were estimated across a range of minimum enlistment standards (or cut scores) to provide Army personnel managers with information about these effects. Specifically, we estimated attrition rates for cut scores ranging from 80 to 120. This particular range of cut scores was selected for two reasons. First, the range selected is comparable to the range of cut scores currently employed by the Army operationally (84 to 110). Second, Army accession policy limits the percentage of accessions falling below AFQT category IIIB who are eligible for military service; presently, around 2%. Because of this, setting the minimum cut score at 80 ensures that information pertinent to all enlisted Soldiers in AFQT categories IIIB and above is represented in the simulation. Doing so accurately reflects the Army's current operational environment, where the overwhelming majority (98%) of its Soldiers fall into these categories.

Type of MOS. MOS meaningfully differ in the nature and complexity of the tasks required for effective performance. Because of this, academic attrition rates will vary by MOS, such that attrition rates will tend to be higher (or lower) for some MOS than others. To show the effects of changes in enlistment standards on academic attrition across the full range of Army MOS, we estimated attrition rates by varying key parameters that reflected operational

differences in MOS. Specifically, we varied parameters reflecting differences in training difficulty and job complexity.[8] A brief description of each appears below.

1) *Training difficulty.* Operationally, training for some MOS is more difficult than others because of the standards, length or content of its training program. To reflect substantive differences in training difficulty, we varied a regression parameter (the intercept) for predicting test scores. Higher intercepts reflect less difficult MOS, whereas lower intercepts reflect more difficult MOS. Conceptually, the level of the intercept represents how well people would be expected to perform independent of cognitive aptitude. In other words, it reflects average training performance as a function of training difficulty. Training difficulty is expected to be positively related to attrition rates, such that higher levels of difficulty produce higher attrition rates.

2) *Job complexity.* Like civilian jobs, the occupational requirements of MOS vary in their complexity. To reflect substantive differences in job complexity, we varied AA composite-training performance validities, as performance validities will vary by MOS (e.g., Scholarios et al., 1994; Statman, 1993). These differences reflect meaningful differences in the content of the job (Guion, 1998; Schmitt & Chan, 1998; Zeidner, Johnson, & Scholarios, 1997). For example, past research has shown that lower validities between aptitude tests and training performance are associated with jobs low in cognitive complexity, whereas higher validities are associated with more cognitively demanding jobs (Hunter & Hunter, 1984). Job complexity is expected to contribute to attrition rates, such that jobs high in cognitive complexity produce lower attrition rates, while jobs low in cognitive complexity disproportionately produce higher attrition rates. Conceptually, this comes about because applicants scoring higher on an aptitude test are more likely to be selected into or attracted to more complex jobs, owing to larger aptitude-performance validities. As cognitive aptitude is positively related to training performance (Carretta & Ree, 2000; Earles & Ree, 1992; Hunter & Hunter, 1984; Olea & Ree, 1994; Ree, Carretta, & Teachout, 1995; Ree & Earles, 1991; Schmidt & Hunter, 1998), more cognitively complex jobs, by having a larger proportion of high aptitude trainees, should display lower overall levels of academic attrition.

   Two points should be emphasized regarding our handling of job complexity in the simulation. First, for our simulation, we did not model the aforementioned selection / classification process. Therefore, for purposes of our simulation the relationship between aptitude-performance validities and attrition is direct and represents a mathematical construction. This means that our simulation results do not reflect the

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[8] In varying these parameters, we kept other parameters (e.g., regression weights) fixed. An advantage to this approach is that it simplifies estimation and interpretation. A disadvantage is that operationally, the fixed parameters will change as a function of differences in the parameters we varied. Therefore, readers should focus on the *pattern* of estimated attrition rates as a function of the variables selected, and not the *levels* of the attrition rates. Additionally, while the number of tests required to complete training will vary across MOS, this parameter was kept fixed to the number of tests required for the particular MOS on which the computer-generated samples were based. This was done to simplify interpretation of results related to training difficulty and job complexity.

actual aptitude distribution of trainees within an MOS, which is technically fixed within the simulation. Nevertheless, the function of that relationship in our simulation is entirely consistent with the underlying selection / classification mechanism not modeled. Second, readers should note that our results for job complexity could be interpreted in one of two ways. They can be interpreted as reflecting differences in attrition rates for MOS that vary in levels of job complexity, as complexity is meaningful associated with differences in aptitude-performance validities, which is our primary intention. Alternatively, results can be interpreted as reflecting operational differences in aptitude-training performance validities (e.g., differences in validities given a fixed MOS). Either interpretation is technically correct. As the primary aim of the study is to inform policy, however, we will emphasize the first interpretation in discussing the results and their implications.

In summary, the simulation conducted reflected a mixed design, with school size (*N*) and minimum enlistment standards as within-group (or repeated) factors, and training difficulty and job complexity as between-group factors. This information is summarized in Table 1.

Table 1
Design of Simulation

	Job Complexity		
Training Difficulty	Low	Medium	High
Low	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)
Medium	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)
High	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)	• *N* (100, 200, 400, 800, 1600, 3200) • *Cut Score* (80-120)

Procedure for Simulating Attrition Rates under Different Operational Scenarios

After identifying the operational scenarios of interest to Army personnel managers, we simulated academic attrition rates under these different scenarios. This section is organized as follows. First, we briefly describe how attrition data for the computer-generated samples were constructed from synthetic training performance data. Second, we briefly outline the procedure for simulating attrition rates under the different operational scenarios described in the previous section.

Constructing Attrition Data from Synthetic Training Performance Scores. We created a dichotomous outcome variable reflecting academic attrition of simulated trainees based on their synthetic training performance scores. The values for this variable were assigned as follows. If

a simulated trainee did not score above the specified minimum passing score[9] (after two attempts) for one or more of the training tests, he or she was coded as an academic attrition ("1"); if all tests were passed, the trainee was coded as *not* attriting ("0"). Because information on retests could not reliably be reconstructed from existing data, we simulated trainee retest behavior by assuming that the two test attempts were statistically independent. Given that retraining of applicants who failed the first attempt is likely designed to give them a better chance of passing the second attempt, the assumption of independence between two attempts is expected to lead to slightly more conservative (i.e., higher) attrition estimates.

Prior to running the full simulation, we calculated overall attrition rates for the synthetic samples generated during the pilot simulation by counting the number of simulated trainees who failed to pass a test (after a second attempt) divided by the total number of trainees (e.g., total sample size). We also computed these rates for a simulation modeling a single attempt. These simulated attrition rates were then compared to the observed attrition rate from our real-world data.

The simulated attrition rates from modeling two attempts ranged from 12-13%. These rates were comparable to the real world attrition rate of roughly 12%. Interestingly, there was a substantial difference in the simulated versus real world attrition rates when simulated trainees were only allowed a single attempt to pass each test (e.g., no retests) versus two attempts. Modeling the two attempts resulted in an attrition rate significantly closer (12-13% versus 40-45% when modeling a single attempt) to the actual, real world rate. Additionally, the simulated rates from modeling two attempts were somewhat higher (about 1%) than the actual attrition rate. This is consistent with our expectation that assuming independence would produce more conservative (higher) estimates, although materially the difference does not appear substantial. Most likely, this is due to the fact that the percentage of trainees requiring more than a single attempt for at least one test is generally small. Taken together, these findings lend confidence to the reliability of our procedure for simulating retest behavior, assuming independence across re-tests.

Simulating Attrition Rates under Different Operational Scenarios. As discussed earlier, a major advantage of our simulation-based approach is the ability to assess error in estimated attrition rates and to demonstrate its impact on the operational decisions Army personnel managers make about where to set minimum enlistment standards. This was accomplished by generating multiple synthetic samples at varying sample sizes based on parameters that reflected different operational conditions Army managers are likely to encounter in the field. Simply put, while the synthetic samples reflect the properties of the MOS used to generate them, they are *not* exact replicas of that MOS. The parameters used to generate the synthetic samples represent population-level information, whereas each synthetic sample reflects the characteristics of a particular sample randomly drawn from that population. Because error is built into these estimations, there is sample-to-sample variability in the properties of the synthetic samples. Therefore, the samples behave in much the same way that randomly selected samples would

[9] All tests were fixed at the same passing score. This was done for two reasons: first, to simplify estimation; and second, because this information could not be reliably obtained from available data.

behave in the real world. The larger its sample size, the more a synthetic sample will approximate the properties of the corresponding population (e.g., the parameters on which the sample was based). The smaller its sample size, the less a synthetic sample will approximate the properties of the corresponding population. By generating multiple synthetic samples, we were able to model the adverse effects of error on estimated attrition rates, so as to provide practical recommendations on these effects when making critical operational decisions.

As reflected in Table 1 above, there were a total of nine conditions (e.g., Low Difficulty, Low Complexity) in our simulation. In estimating academic attrition rates, the same levels of sample size and range of cut scores were used for all conditions (see Table 1). For technical documentation and accompanying SAS programs, see Appendix D. In brief, for each condition, we conducted the following activities:

1. Using the parameters relevant to a given condition, we replicated 2,000 samples at 6 different sample sizes (e.g., 100, 200, 400, 800, 1600, and 3200); each sample containing synthetic training performance and attrition data. This means that for each condition, we simulated a total of 12,000 samples (6 x 2,000 = 12,000). The properties of these samples approximated the parameters specified, which were meant to reflect the operational conditions Army personnel managers were likely to see on the job. Prior to the simulation, the integrity of the procedure and SAS program for generating the synthetic samples had been successfully verified (see pages 13 - 14).

2. For each of the 2,000 computer-generated samples, we estimated the recommended logistic regression model, by regressing attrition (a dichotomous dependent variable) onto synthetic AA composite scores. These regression parameters became the input for estimating attrition rates.

3. For each of the 2,000 replications, we estimated academic attrition rates, using the regression parameters computed (from Step 2), for a range of cut scores. This was done by sample size (*N*). As discussed previously, the differing sample sizes (*N*) reflected operational differences in school size. The range of cut scores reflected operational differences in minimum enlistment standards.

4. We then averaged the estimated attrition rates across all 2,000 replications for the full range of cut scores by *N*. In the process of averaging attrition rates, we estimated the corresponding standard errors (SEs). When done, average attrition rates and corresponding SEs were compiled and outputted. For each condition, the final output consisted of a single table summarizing average attrition rates (and standard errors) by AA composite cut score and *N* (see Appendix B). The composite utilized in the simulations is General Maintenance (GM).

RESULTS

Results are organized by the factors (school size, range of enlistment standards, training difficulty, job complexity) we varied to reflect the different operational scenarios Army personnel managers were likely to encounter on the job. Tables and Figures referenced in this section can be found in Appendices B and C. Readers should note that the attrition rates reported are estimates based on simulated data and are not associated with a particular MOS. Because of this, the rates reported should *not* be used to make operational decisions for a given MOS, as they do not represent actual MOS school attrition rates. For operational usage, readers are advised to apply the proposed methodology of the current study to available real-world data for the MOS of interest. Recommendations for doing so are detailed in the Discussion section. The SAS program (with documentation) for running an attrition rates analysis using actual MOS school data appears in Appendix E.

School Sample Size (N)

School sample size (N) reflects operational differences in the number of Soldiers trained for a selected MOS. We varied school sample size (N=100; 200; 400; 800; 1600; 3200) to represent levels at which we expected to see substantial, and practically meaningful, differences in the amount of error associated with estimated attrition rates.

As evident from Tables 1 to 9 (see Appendix B)[10], attrition rates do not vary significantly as a function of N. For any given cut score, the estimated attrition rate is generally the same irrespective of N. This trend is most apparent when looking at Figures 1 to 9 (see Appendix C). For example, when viewing Figure 1, one sees that across the full range of cut scores, the estimated attrition rates for the varying levels of N substantially overlap, such that there is basically a single line showing the trend in attrition rates by cut score. Because of the amount of overlap, the lines reflecting the different levels of N cannot be meaningfully differentiated. There are small differences (about .01) in attrition rates by N for some of the lower cut scores, but overall, attrition rates do not vary significantly as a function of N. These findings are not surprising given the large number of synthetic samples (2,000) generated for the simulation. Because of the large number of synthetic samples, the average attrition rate reported in Tables 1 to 9 should approximate that of the corresponding population (or "true") attrition rate.

The above findings should *not* be interpreted to mean that N will *not* impact the observed attrition rate estimated from a sample of MOS school data, as would be the case when this analysis is performed operationally. Rather, these findings suggest that estimated attrition rates are not expected to be *systematically* biased in one direction or another (e.g., estimated attrition rates will always be higher or lower than the "true" attrition rate). The impact of N on school

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[10] Please note that when the cut score was high for some of the conditions (e.g., low difficulty, high complexity) so that the estimated attrition rate is close to zero, several of the 2,000 replications for the smaller sample sizes (N=100 or 200) were not included in the estimation of the average attrition rate (and SE) because there was no attrition on which to base estimates. Because the percentage of replications dropped (out of the total) was generally small and zero attrition is practically not going to be a concern to Army managers, we did not correct this.

attrition rates (estimated from sample data) is best examined with the standard error (SE), which measures the variability of these estimates from sample to sample. Operationally, the amount of SE matters because it speaks to the precision of estimated attrition rates. For example, if the observed attrition rate is .13 (or 13%) and the SE is .04, then the "true" attrition rate could be anywhere from .05 (5%) to .21 (21%) within generally accepted levels of statistical confidence (about 95%). Clearly, the decision made about where to set enlistment standards would vary considerably depending on which of these values (i.e., 5% vs. 13% vs. 21%) most accurately reflects the "true" attrition rate.

As can be seen from Tables 1 to 9, it is apparent that as *N* increases, the precision (as reflected in the SEs) of the estimates increases, as expected. More specifically, looking at Figures 10 to 18, one sees two notable trends regarding the behavior of SE. First, SE is inversely related to *N*, such that as *N* increases, SE decreases. From $N = 100$ to 200, SE is large and the reduction in SE (from $N = 100$ to 200) is modest, roughly 26 - 35% (see Figures 19 - 27). Moving to $N = 400$ further reduces SE (about 48 - 55% from $N = 100$), but the resulting SE is still large relative to the attrition rate. Starting at $N = 800$, we start to see a meaningful reduction in SE (about 62 - 69%), that progressively levels off as *N* doubles from 800 to 1600 (74 - 79%) and then again to 3200 (81 - 83%).

The second trend evident from Figures 10 to 18, is the relationship between SE and cut score. Specifically, as the cut score is raised, SE decreases. However, this decrease in SE is largely a consequence of the corresponding decrease in the magnitude of attrition rates. That is, smaller absolute standard errors are expected when estimating the lower attrition rates associated with higher cut scores. This is more visible when looking at Figures 28 to 36. As can be seen from these figures, the amount of SE relative to the magnitude of the attrition rate (reflected in the coefficient of variation) appears to be uniform across the cut score range except at the highest, most extreme score in the range (where AA = 120).

In summary, school size significantly impacts the level and accuracy of attrition rates estimated from sample school data. Most importantly, these estimates are likely to be less biased and more precise with larger *N*. This relationship can have major implications for the operational decisions Army personnel managers must make regarding where to set minimum enlistment standards.

Range of Minimum Enlistment Standards

The range of minimum enlistment standards reflects operational differences in the criticality of the job or accession goals associated with a targeted MOS. We simulated attrition rates across a range of cut scores (80 to 120) Army personnel managers are likely to use operationally when setting enlistment standards.

As expected, the raising (or lowering) of cut scores is meaningfully associated with academic attrition, such that attrition rates are higher when cut scores are lower. Referring back to Tables 1 to 9, and Figures 1 to 9, and ignoring other factors (e.g., training difficulty, job complexity), one sees that attrition rates steadily decline as the cut score increases. This trend holds for all levels of *N*. For example, looking at Figure 5, the attrition rate (with corresponding cut score in parentheses) drops from .30 (80) to .15 (100) to .05 (120). Likewise, as the cut score

increases, the SE decreases (see Figures 10 to 18); although, as reported in the preceding section, the size of SE relative to the underlying attrition rate generally appears to be uniform.

In summary, estimated attrition rates are related to cut scores, such that higher cut scores are associated with lower attrition rates. However, the relative precision of these estimated attrition rates appears constant across cut score. At an operational level, this means that the accuracy of sample-based attrition rates is expected to be about the same irrespective of cut score.

Training Difficulty

Operationally, the training difficulty of MOS will vary because of differences in the standards, length, or content of training. We varied a regression parameter (the intercept) for predicting test scores to reflect low, medium, and high training difficulty. This enabled us to project academic attrition across a range of MOS that varied in training difficulty, just as MOS would in the field.

As expected, academic attrition meaningfully varies as a function of training difficulty. As can be seen in Tables 1 to 9 and Figures 37 to 40, and ignoring other factors (e.g., job complexity), attrition rates are higher when training difficulty is high, and lower when difficulty is low. For example, looking at Figures 37 to 40, one sees that attrition rates are consistently related to training difficulty, irrespective of N and cut score, such that greater training difficulty is associated with higher attrition rates. However, the differences in attrition rates by training difficulty progressively get smaller as the cut score increases. For example, where $N = 400$ (see Figure 38), estimated attrition rates differ, on average, about .15 (15%) for a cut score of 80, about .12 (12%) for a cut score of 100, and .05 (5%) for a cut score of 120.

There are two trends to note related to the estimated SE (precision) of observed attrition rates (see Figures 41 to 43). First, SE varies by N, irrespective of cut score. Consistent with earlier findings, and as expected, the SE drops as N increases. This trend holds for all levels of training difficulty. The second trend of note is that the SE, on average, is smaller when training difficulty is high, except for the upper cut score range (e.g., 100 - 105). Likewise, except for the lower cut score range (e.g., 80 - 85), SE is higher, on average, when training difficulty is low. This is unusual, as we expect SE to reflect differences in the magnitude of the attrition rates between difficulty levels (e.g., lower attrition rates should be associated with lower SE, and higher rates with higher SE).

In summary, consistent with our predictions, attrition rates are substantively related to training difficulty, such that the more difficult the training the lower the attrition. The relative precision of the attrition rate estimates (reflected by SE) appears to be relatively equivalent across difficulty level, particularly at higher levels of N. Practically, this means that sample-based attrition rates are expected to exhibit similar levels of imprecision irrespective of the difficulty level of the targeted MOS. We consider the practical implications of these findings further in the Discussion section.

Job Complexity

Like civilian occupations, Army MOS vary in their complexity. To reflect substantive differences in job complexity, we varied AA composite-training performance validities to reflect meaningful differences in the content of the job. Specifically, past research has shown that lower validities between aptitude tests and training performance are associated with jobs low in cognitive complexity, whereas higher validities are associated with more cognitively demanding jobs (Hunter & Hunter, 1984). As with training difficulty (see above), varying performance validities enabled us to simulate attrition rates for the full range of MOS Army personnel managers will encounter operationally.

As predicted, academic attrition is meaningfully related to job complexity, although there are some patterns related to SE that we thought were unusual. As can be seen in Tables 1 to 9 and Figures 44 to 47, and ignoring other factors (e.g., training difficulty), attrition rates are generally higher when cognitive complexity is low, and lower when cognitive complexity is high. As a specific example, looking at Figures 44 to 47, one sees that attrition rates are meaningfully associated with cognitive complexity, irrespective of *N* and cut score, such that greater cognitive complexity tends to correspond to lower attrition rates. Unlike training difficulty, the relative drop in attrition rates across the cut score range is substantially greater when job complexity is higher. For example, in the middle cut score range from 90 through 110, the 17-point drop (from 49% to 32%) represents a 35% relative decrease in attrition. In contrast, the 14-point drop (from 23% to 9%) and 16-point drop (from 18% to 2%) for medium and high job complexity, while not too different in comparison to the 17-point drop for low complexity, represent, respectively, 61% and 89% decrease in attrition. These observations are consistent with the higher discrimination power possible with higher validities.

Comparable to the findings for training difficulty, there are two trends worth noting with respect to the estimated SE (precision) of observed attrition rates (see Figures 48 to 50). First, as expected, the SE decreases as *N* increases irrespective of cut score. This trend holds for all levels of cognitive complexity. A second trend that was quite unusual is that the SE is greater for high complexity compared to low complexity jobs in the lower cut score range (e.g., 80 - 85), but is lower in the higher cut score range (e.g., 100 - 105). This trend holds even though the attrition rate for high complexity jobs is consistently lower compared to low complexity jobs. This is unusual in that we typically associate lower SE with the lower magnitudes of attrition rate.

In summary, there is a significant relationship between job complexity and attrition rates, such that (generally) the more complex the job the lower the proportion of Soldiers failing to successfully complete training requirements. Equally important is that the relative drop in attrition associated with increasing the cut score is substantially greater for higher validities or job complexity. Please note that operationally all these findings can also be interpreted as applying to differences in AA composite-training performance validities (low, medium, and high), as validities will likely vary across MOS within the same level of complexity.

DISCUSSION

To facilitate our discussion, this section is organized into three main parts. First, we place the results of our simulation in context, by integrating our findings on the effects of raising (or lowering) enlistment standards on academic attrition. In particular, we consider the practical implications of these findings. Second, we provide concrete recommendations for conducting analyses of attrition rates operationally. Specifically, we make recommendations regarding: (a) the collection and identification of requisite data for analysis; (b) planning an attrition rates analysis; and (c) interpretation of the effects of adjusted cut scores on attrition. These recommendations are meant to serve as a guide to Army researchers and personnel managers responsible for performing attrition rates analysis for decision-making purposes. Finally, we conclude our discussion by making suggestions for future research.

Effects of Changing Minimum Enlistment Standards on Academic Attrition

Results from our simulation showed that, consistent with previous research (e.g., Carretta & Ree, 2000; Earles & Ree, 1992; Hunter & Hunter, 1984; Olea & Ree, 1994; Ree et al., 1995; Ree & Earles, 1991; Schmidt & Hunter, 1998), cognitive aptitude is a good predictor of training performance. This finding extends recent Army research on the validity of the new AA composites (e.g., Zeidner et al., 2000) by using an updated database and a criterion specific to training success. Therefore, knowledge of enlisted Soldiers' cognitive aptitude, reflected operationally in AA composite scores, is a useful tool for informing training decisions. Practically, this means that the setting of minimum enlistment standards can (and should) impact the level of academic attrition. Consistent with this, our results confirmed that, in general, raising enlistment standards decreases academic attrition, while lowering these standards increases attrition. However, when interpreting this tendency, decision-makers should be cautious, as it depends on several factors. These factors could significantly impact how the effects of raising (or lowering) enlistment standards on attrition rates are interpreted and, thereby, what decision is best for achieving a desired level of attrition. These factors and their practical implications are as follows.

First, the level and rate of change in attrition is dependent on the MOS. Specifically, MOS vary in training difficulty and job complexity. (Readers are reminded that statements made about job complexity apply equally to AA composite-training performance validities.) These characteristics impact academic attrition. For example, attrition rates will be higher for MOS whose training is more difficult (apart from cognitive requirements); and attrition rates will likely be higher for MOS whose job requirements are less cognitively demanding (as discussed earlier). This means that for some MOS reducing academic attrition, by way of enlistment standards, may be operationally difficult. For these MOS achieving targeted levels of attrition rates may be infeasible, as they would require a substantial raise (or drop) in enlistment standards that would not be feasible for operational reasons (e.g., accession goals). For example, for MOS where training difficulty is high, reducing attrition rates by 50% would necessitate a roughly 20 to 25-point adjustment in the requisite cut score; reductions of 33% (one-third) would require a 10 to 15-point adjustment. While major reductions (e.g., 10% or more) in attrition rates require significant changes in enlistment standards for all MOS, for some MOS reaching a particular (low) level of attrition or achieving a substantial drop in attrition is especially problematic. One

potential explanation of why academic attrition is higher in some of the simulated MOS than others, specifically those low in job complexity, is that cognitive aptitude appears to carry limited utility as a predictor of training success. Operationally, this also leads to a greater percentage of person-job mismatching between trainees and MOS, which could additionally contribute to attrition.

In practical terms, these findings suggest that reducing or reaching a desired level of academic attrition in some MOS (e.g., those with high training difficulty, those with low job complexity) may be best achieved by methods other than adjustments in minimum enlistment standards, from which it follows that training decisions could be greatly improved, particularly for some MOS, by incorporating information other than cognitive aptitude into personnel and assignment decisions.

A second factor that substantially impacts the interpretation of attrition rates is school sample size (*N*). Operationally, MOS attrition rates observed and reported to Army managers for making personnel decisions, such as setting minimum enlistment standards, are sample-based estimates, as opposed to the population attrition rates, and therefore, contain error. For instance, looking at Table 5, $N = 200$ and a cut score of 95, one sees that the estimated attrition rate is .19 (19%). However, treating this as the sample-based estimate it is, when we take into account error (measured by the standard deviation of the estimated attrition rate), the true attrition rate is really anywhere from .11 (11%) to .27 (27%). This is extremely important from an operational perspective.

To illustrate, consider that an Army personnel manager's goal is to achieve an academic attrition rate of 15%. The observed attrition rate, based on available sample data (N=200), is presently around 19%. On its face, this means that attrition is currently off by about 4% from the designated target. To reach his/her specified goal (15%), the manager will most likely need to increase the cut score, so as to reduce attrition by the desired amount (4%). This translates into a 5 or 6-point increase in the current cut score. However, if error is taken into account, we see that the "true" attrition rate is actually somewhere between 11% and 27%. This suggests that attrition could already be at the targeted level (15%), in which case an increase in the current cut score is not needed. On the other hand, it also suggests that attrition is potentially worse than it appears (over 19%), in which case a *bigger* increase in the cut score is needed to reach the manager's operational goal with confidence. The course of action the Army manager should take depends on which of these scenarios is "correct." However, it is difficult to tell which scenario is most "correct", given the level of error (and inaccuracy) in the observed attrition rate. This is not trivial, since raising the cut score (to lower attrition) comes with a potential tradeoff in meeting accession goals. If MOS attrition is already at its targeted level, then increasing the cut score could adversely, and unnecessarily, impact accession goals; a tradeoff, which in this case, a manager did *not* have to make. More precise estimates of these rates would ultimately make this decision-making process easier and would avoid forcing managers to make poor decisions.

The point raised in the example above is that we can never be 100% sure about the "true" attrition rate for a given cut score from sample data. Consequently, what changes in the cut score are needed to achieve a targeted attrition rate is never certain. Fortunately, however, the level of uncertainty associated with cut score changes goes down as the sample size is increased. To illustrate, we continue the example above by referring to Figures 51 and 52. The points on

the curve represent the "true" attrition rate that is unknown and unobservable from sample data. The vertical bars represent the likely range of attrition rate estimates that we are going to actually observe using sample sizes of 200 or 800. (Note that the end points of the vertical bars are two SE from the center; approximately, there is 95 percent probability that the estimated attrition rates fall within the interval.) The potential observed rates represented by the vertical bars will become the basis of cut score decisions. Using a sample size of 200, an Army manager will have to raise the cut score to 115 in order to be statistically confident that the attrition rate will be no more than 10%. The interval from 107 to 114 represents "missed opportunities" to set a lower cut score that can achieve the 10% target; this is due to imperfect sample information. Using a sample size of 800, the manager can set the cut score to a lower value of 111 and be equally confident that the attrition rate would be 10% or below. In this case, the interval of missed opportunities is much shorter, from 107 to 110. In other words, increasing the sample size minimizes the missed opportunities to adjust the cut score to the minimum required to achieve a targeted attrition with confidence. Operationally, this means preserving as much of the eligible applicant pool as possible.

In summary, the preceding examples highlight how error can complicate operational decisions: (a) about *whether* to adjust current enlistment standards; and (b) *how much* to adjust these standards to achieve desired objectives.

Results from our simulation show that the amount of error in sample-based attrition rates is strongly related to school sample size (*N*). Specifically, the smaller the sample size, the more inaccurate (and potentially misleading) is the estimated attrition rate based on sample data. The bigger the sample size, the more accurate (and less misleading) is the estimated attrition rate. In practical terms, our findings suggest that the accuracy of sample-based attrition rates is positively related to school sample size (*N*), and decision-making will be greatly improved by taking into account sample size when estimating MOS attrition rates.

Recommendations for Analyzing Academic Attrition Rates

In this section, we detail recommendations for analyzing academic attrition rates estimated from MOS school sample data. Specifically, we make recommendations pertaining to the: (a) collection and identification of data prior to analysis; (b) specification and estimation of a regression model; and (c) interpretation of adjusted cut score effects on attrition rates.

Data Collection

As evident from the preceding discussion (and earlier sections of this report), issues related to the identification and collection of data for these analyses are critical, as the proposed methodology will only be as good as the available data. Our recommendations are divided into two parts. First, we make recommendations dealing with planning an attrition rates analysis (e.g., prior to actually collecting or identifying requisite data). Second, we make recommendations related to the collection and/or identification of data for analysis.

Planning an Attrition Rates Analysis. Prior to collecting or identifying data for analysis, it is important to carefully consider school sample size (*N*) and magnitude of desired change (increase or decrease) in attrition. It is strongly recommended that (any) analyses not take place

without addressing these issues. Considering school sample size and magnitude of the desired change in attrition will minimize error and maximize the relative precision of estimated attrition rates. Operationally, this will enhance the decisions made by Army personnel managers and strategic planners.

With respect to school sample size (*N*), our simulations show that small sample sizes (N<200) are problematic because estimated attrition rates based on these sample sizes are associated with a large amount of error. As a result, we recommend that, where possible, analyses not be conducted on *N's* less than 400. For best results, we recommend an *N* of 800. There are two reasons why we prefer an *N* of 800. First, an while *N* of 400 reduces error by about 50% (from an $N = 100$), an N of 800 cuts error, on average, by two-thirds (see Figures 19 to 27). That represents a considerable gain in precision, over and above that expected for an *N* of 400. Second, and related to this first point, there is a tradeoff between *N* and practical data collection and quality control (QC) issues. Although, the bigger the *N*, the smaller the error, larger sample sizes are not always practically feasible, due to limited time and resources. In addition, larger sample sizes are associated with increased data management and QC issues (e.g., more time spent managing data, greater percentages of missing or inaccurate data). For these reasons, there is a point of diminishing returns, where a higher *N* does not yield substantially new information. For example, for sample sizes from 100 to 800, every increase in *N* by 100 produces an (average) reduction in error of about 8%. From sample size 800 to 1600, the (average) reduction drops to 1-2%. For sample sizes from 1600 to 3200, the (average) reduction drops even further to less than 1% (for every increase in *N* of 100). This trend is visible in Figures 19 to 27. As evident from these figures, doubling the sample size results in progressively smaller reductions in error, going from roughly 30% ($N = 100$ to 200) to 20% ($N =$ 200 to 400) to 15% ($N = 400$ to 800) to 10% ($N = 800$ to 1600) to 7% ($N = 1600$ to 3200). In summary, there is a point where the costs of greater *N* (e.g., time collecting data) outweigh the benefits (e.g., smaller error), and that point appears to be around an *N* of 800.

Having made the above recommendations, we acknowledge that an *N* of 800 (or even 400) may not always be feasible, particularly for MOS that train small numbers of recruits ($N <$ 50) per year. For those MOS, we suggest the following. First, we advise combining data from multiple fiscal years (FYs) to achieve a preferred level of *N*. Second, if combining multiple FYs is not practical, we suggest combining data from comparable MOS (e.g., similar training and job requirements). The procedures for identifying comparable MOS are beyond the scope of the present study, but procedures are available within the applied personnel psychology literature for synthesizing data from multiple jobs for purposes of making personnel decisions. This particular suggestion holds for MOS that are new and for which there is little to no historical data from previous FYs. Third and finally, should less than preferred levels of *N* be available, we recommend that school proponents and Army personnel managers be conservative when interpreting estimated attrition rates.

The second factor to consider prior to performing an attrition rates analysis is the desired change (increase or decrease) in the attrition rate. We recommend not targeting a change in attrition arbitrarily. This is important because the magnitude of the desired change (large or small) will impact how high or low the cut score should be adjusted to achieve the desired attrition rate. The size of the prospective training pool is impacted the more one has to adjust the cut score to be reasonably confident that a targeted change in attrition will be achieved. From an

operational perspective, this is not trivial since inadvertently excluding enlistees from an MOS's training pool could decrease the number of eligible enlistees in the pool and adversely impact one's accession goals. For instance, using the earlier example, the cut score needed to be adjusted to 115 or 111 if using samples sizes 200 or 800, respectively, to be confident that the true attrition rate is not more than 10 percent. Suppose the current cut score is 104, for which approximately 42% of the youth population is eligible.[11] Then the percentage of the eligible pool will drop by 19 percentage points (from 42% to 23%) if the cut score is adjusted to 115, but will only drop by 13 percentage points (from 42% to 29%) if it is adjusted to 111. The latter is closer to the minimum possible drop of six percentage points (from 42% to 36%) if we have perfect information and are able to adjust the cut score to 107, which would yield the 10% targeted attrition rate.

In summary, given a fixed target attrition rate, the sample size (*N*) chosen for analysis represents a trade-off between the short-term costs associated with data collection and management versus the long-term savings related to recruiting, that is generally made possible by not having to substantially increase the cut score.

Collecting or Identifying Requisite Data. Once the school sample size and desired change in attrition have been addressed, data can be collected, or alternatively, existing data may be identified for performing the attrition rate analysis. The issues to be considered at this stage are: (a) the number of training classes to include in the analysis; (b) accuracy of data; (c) missing data; and (d) criterion contamination.

First, regarding the number of classes to include in the analysis, most likely data will need to be collected from multiple classes to reach recommended levels of *N* (e.g., 400 - 800). Practically, classes currently in session should be excluded from the analysis. An important statistical issue related to multiple classes is the non-independence of observations from trainees belonging to the same class, and potentially, across classes. This non-independence could be due to a variety of factors, such as multiple classes having the same instructor. Non-independence, if not addressed, could underestimate error. The present methodology does not take this into account, but future research on this issue is highly recommended.

Second, with respect to the accuracy of collected or existing data, there are several steps that can be taken to ensure data integrity. These steps are extremely important, as the quality of the data will significantly impact the results of any analyses, and operationally, decisions made based on the results. Prior to data collection, it is recommended that efforts be made to standardize data collection and minimize potential data entry errors. These could include standardizing data entry protocols, the development of a single database to which all data will be entered, or the creation of fields for screening data for errors upon entry (where the distance between the original data source and the recorded data is shortest). Post-data collection, it is highly recommended to perform a set of data screening (or QC) procedures. These procedures

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[11] This approximation is based on a normally distributed AA score with mean equal to 100 and standard deviation of 20.

would include checking for out-of-range values and missing data.[12] If data screening identifies significant problems, additional data collection may be warranted. In general, it is best if these problems can be avoided up front by taking steps (see above) to minimize potential problems as data are collected. In the long run, doing so will substantially reduce the time and resources expended in collecting data.

Third, specific to missing data, those performing attrition rates analysis are advised to check the percentage of cases missing data and to examine the nature of missing data (e.g., random versus not random). Sizeable percentages of missing data are problematic because they could contribute to estimation problems when running the analysis. Likewise, data not missing at random could seriously bias results, as the cases with complete data may differ significantly from those missing data.[13] Where possible, and the accuracy of doing so can be verified using available data, it is recommended that missing data be filled in prior to analysis. This may not always be possible, but can be done when necessary data are available. For example, if data on output codes are missing for some cases but complete training performance data is available, the correct output code can be imputed based on the existing data and knowledge of the cut scores for the different training tests (e.g., a failing grade on at least one of the tests results in the trainee being classified as "attrit"). Generally, it is preferable if missing data can be avoided by taking steps to minimize incomplete records when data are collected.

Fourth, those performing an attrition rates analysis are likely to encounter possible criterion contamination. This occurs when a trainee's output code is inconsistent with training performance data (e.g., trainee failed one or more tests, but output code indicates that the student graduated). There are several reasons why criterion contamination may be present (e.g., data entry error, trainee warrants special exemptions). Irrespective of the reason, criterion contamination is problematic in that it biases results. To reduce the potential bias resulting from criterion contamination, it is recommended that: (a) non-academic attritions be excluded from the analysis; and (b) the alignment between output codes and training performance data be checked for discrepancies (e.g., output code indicates trainee graduated, but training performance data shows that he/she did not pass one or more tests). When verifying the integrity of the output codes, check if the percentage of discrepancies matches what is to be expected, as most MOS will probably contain some percentage of trainees passed for special exemptions. If the percentage of cases with discrepancies is within the expected percentage (of total cases), these problem cases can simply be aligned to make the output code reflect the "true" academic training outcome. If the percentage of cases is greater than expected, the integrity of this information is suspect and additional data collection may be warranted.

Interpreting the Effects of Adjusted Cut Scores on Attrition Rates

There are several issues that should be considered when interpreting the effects of adjusted cut scores on attrition rates.

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[12] See Tabachnick and Fidell (1996) for a practical and comprehensive overview of data screening procedures.

[13] See Roth (1998) or Switzer and Roth (2002) for guidelines and suggestions on dealing with missing data.

First, as evident from the results of our simulation, interpretation must account for the impact of school sample size (*N*) on the accuracy and precision of observed attrition rates. It is strongly recommended that this factor be considered when interpreting the results of an attrition rates analysis, as it could substantially influence the operational decisions made by Army personnel managers and strategic planners. Accuracy and precision considerations also apply when contemplating adjusted cut score effects on personnel outcomes other than attrition rates (e.g., demographic representation). For example, when examining other personnel outcomes in conjunction with attrition rates, the same issues (e.g., error, magnitude of expected change) are pertinent and should be taken into account when interpreting these effects.

Second, it should be noted that *not* all attrition is intrinsically "bad." This is why a 0% attrition rate is not a meaningful (or practically feasible) operational goal. To some degree, the seriousness of attrition rates depends on *who* is failing to complete training. For example, if those failing to complete training are poor quality recruits not likely to complete their first-term enlistment or satisfactorily meet minimum performance standards, then attrition is serving a functional, healthy purpose. It is possible that there is a level at which attrition is *positively* contributing to overall mission performance (as a whole). We recommend that this point be considered when both determining the expected change in attrition and when interpreting adjusted cut score effects.

Finally, it is advisable to consider if changing cut score is always the best available means for managing academic attrition. Operationally, altering MOS cut score is just one of several strategies (e.g., adjusting passing grades, revising content and delivery of training, shortening the number of tests required to graduate, etc.) for minimizing attrition. As seen from our simulation, substantial reductions (e.g., 33%-50%) in attrition are practically not feasible without major adjustments in minimum enlistment standards. Therefore, to achieve desired levels of attrition, it is recommended that Army personnel managers and strategic planners consider combining cut score adjustments with other personnel management strategies. This may be particularly advantageous when lowering the cut score to meet accession goals, as decreases in enlistment standards are associated with increases in attrition rates. It may be possible to mitigate these increases by implementing proposed cut score adjustments in combination with other strategies.

Suggestions for Future Research

The following are suggestions for future research that would further enhance our understanding of training attrition and the effects of changing minimum enlistment standards for the Army (as a whole). These suggestions would greatly contribute to our knowledge of factors contributing to attrition, and more practically, improve the decision-making of Army personnel managers and strategic planners.

Expanding the Model for Informing Related Personnel and Training Decisions

For the present study, the primary goal was to model the effects of changes in enlistment standards on academic attrition for purposes of informing the setting of these standards. However, Army school proponents, personnel managers, and strategic planners may be interested in extending the current model to inform other related personnel and training

decisions. For example, as evident from our results, for some MOS, understanding the effects of enlistment standards on attrition may not be especially informative for determining how best to minimize attrition. Therefore, school proponents of those MOS may be interested in understanding the effects on attrition when qualification standards other than cognitive aptitude (e.g., medical status) are adjusted. Likewise, strategic planners may be interested in assessing the effects of changes in enlistment standards on accession goals for different demographic groups. Both of these examples, along with others, could be addressed by extending the current model to include variables other than cognitive aptitude. The following are variables that could be added to the current model for purposes of supporting personnel and training decisions related to the current model's purpose.

While cognitive aptitude is a good predictor of training performance (e.g., Earles & Ree, 1992; Hunter & Hunter, 1984; Olea & Ree, 1994; Ree & Earles, 1991), in many cases failure to complete training is *not* a function of lack of ability (Ree & Carretta, 1999). One candidate that might account for attrition beyond cognitive aptitude is educational status. Historically, military studies show that educational status, specifically high school completion status, is the single best predictor of first-term attrition, even after controlling for age, cognitive aptitude, and other personal characteristics (Laurence, 1984, 1987; Laurence, Naughton, & Harris, 1995). There are two possible explanations for this.

First, the types of competencies and skills necessary to complete a regular high school diploma (or two full years of college) may be similar to the skills predictive of training success. By earning a regular high school diploma, or other educational credential requiring a similar degree of discipline and persistence (e.g., college), an individual has demonstrated the ability to learn in a formalized and highly structured environment, an environment comparable to that of Army training programs.

A second potential explanation for the relationship between educational status and attrition is that educational completion status is a surrogate for attributes besides cognitive aptitude, such as motivation or personality. An extensive body of research shows that these characteristics are predictive of job and training performance across a variety of occupations (Barrick & Mount, 1991; Barrick, Mount, & Judge, 2001; Hough & Furnham, 2003; Judge & Ilies, 2002). In addition, there is strong evidence that these characteristics meaningfully add to the prediction of job and training performance over and above cognitive aptitude (Hough & Furnham, 2003; McHenry, Hough, Toquam, Hanson, & Ashworth, 1990; Schmidt & Hunter, 1998). These findings suggest that assessing characteristics beyond cognitive aptitude could greatly contribute to predicting training performance.

Medical and health-related factors constitute another potential candidate for inclusion in models of training attrition (Laurence et al., 1995). For example, in a recent study with Navy recruits, researchers found that self-reported medical and health-related factors were stronger predictors of first-term attrition than educational status or cognitive aptitude (Larson, Booth-Kewley, & Ryan, 2002). This finding is consistent with recent U.S. government reports on military screening practices emphasizing the role of medical and health-related factors in attrition (U.S. General Accounting Office, 1997; 1998; 2000). These factors may be especially pertinent to predicting success in MOS requiring high levels of physical and mental endurance, and for predicting attrition during training due to non-academic reasons.

In summary, expanding the current model to include factors beyond cognitive aptitude as predictors could greatly benefit Army personnel managers and strategic planners. Extending the model will aid decisions on how best to reduce attrition, particularly when changes in enlistment standards may be insufficient for achieving a targeted level of attrition.

Predicting Trainee Re-Test Performance

Operationally, trainees have the opportunity to retake tests that they failed to pass on the first attempt. Specifically, trainees are permitted a second attempt for all required tests not passed when first administered. The present study simulated retest behavior assuming independent test attempt, as we were unable to examine the factors contributing to retest performance. Knowledge of factors explaining retest performance could be incorporated into the attrition model and, consequently, improve its predictive performance.

Possible factors that account for retest success, include those factors mentioned above (e.g., education, motivation, personality, medical/health-related variables), plus variables such as self-efficacy. Self-efficacy reflects an individual's beliefs about his/her task capabilities, and has been shown to be a powerful predictor of learning and training performance (Cannon-Bowers, Salas, Tannenbaum, & Mathieu, 1995; Gist, Schwoerer, & Rosen, 1989; Martocchio, 1994; Mathieu, Martineau, & Tannenbaum, 1993; Salas & Cannon-Bowers, 2001). Research shows that features of the training environment (e.g., method, content, instructor), in particular the feedback trainees receive, can contribute to a trainee's self-efficacy and subsequent performance (Cannon-Bowers et al., 1995; Eden & Ravid, 1982; Gist et al., 1989; Mathieu et al., 1993). Practically, this is valuable to know, since in the long run, it may be more cost-efficient for the Army to develop and implement guidelines for delivering effective training feedback Army-wide (and thereby, benefit the Army as a whole), as opposed to instituting changes in minimum enlistment standards for individual MOS. Further, as self-efficacy has been identified as a means for reducing group differences in test performance (e.g., Hough, Oswald, & Ployhart, 2001; Sackett, Schmitt, Ellingson, & Kabin, 2001), these strategies may prove beneficial in achieving the demographic representation Army personnel managers seek for targeted MOS, without sacrificing overall performance.

Modeling Adjustments to Minimum Enlistment Standards from a Multiple Job Context

Most training research, the present study included, produce results that are framed in a single job context. How well these findings apply to a multiple job context (e.g., Zeidner et al., 1997), such as the Army's, is less clear. Future research would benefit from investigating and modeling issues of interest to Army personnel managers (e.g., setting minimum enlistment standards) from a multiple job context. In particular, future research that examines these issues from a more macro perspective, like that evident in classification research (e.g., Johnson et al., 1992; Zeidner et al., 2000), would be informative. For example, future research should consider how adjustments in cut scores for one MOS impact the attrition rates of other MOS. Related to this work would be the development and validation of methodologies for maximizing a criterion, comparable to overall performance (e.g., MPP) that characterizes military classification research.

Modeling the Relationship between Training and On-the-Job Performance

Future research might consider the potential tradeoffs between training attrition and subsequent job performance for the Army as a whole. These tradeoffs (and their effects) are presently missing in both Army training and classification research. For instance, setting high enlistment standards will likely increase the percentage of rejected applicants (for the Army as a whole), but will also likely increase overall job performance, as the more capable Soldiers are retained and receive high quality training. Alternatively, lowering enlistment standards may reduce the percentage of rejection, but at the same time negatively impact overall performance, by increasing the retention of poor performers and reducing the overall quality of training that all recruits receive.

Methodologies that model these potential tradeoffs could greatly assist decision-makers in identifying strategies that satisfy operational goals associated with both (e.g., training *and* solder performance on the job). For example, by lengthening or altering the content of its training programs, it might be possible for the Army to both control attrition, while maximizing overall job performance. Practically, this could also translate into lower enlistment standards making it possible for the Army to increase the eligible accession pool and meet accession goals without the associated trade-offs (e.g., Soldier performance). From an operational perspective, these methodologies would be especially important when changes in the Army's recruiting environment make it seem that potential tradeoffs between training effectiveness and Soldier performance cannot be avoided.

Conclusion

Army personnel managers frequently need to make tradeoffs between Soldier numbers, quality, training effectiveness, and a host of other factors when making personnel management and training decisions. The purpose of the present study was to propose and demonstrate a logistic regression-based approach for estimating academic attrition rates from technical training school. This approach enables Army personnel managers and strategic planners to evaluate the aforementioned tradeoffs when making decisions about where to set minimum enlistment standards. To demonstrate the approach, we conducted a large-scale simulation study that simulated attrition rates under different operational scenarios Army managers are likely to encounter on the job. SAS programs (with documentation) for running an attrition rates analysis on MOS school data using the proposed approach are available in Appendix E.

The major findings of our simulation are threefold. First, a simple approach based on logistic regression using only cognitive aptitude information is adequate for evaluating the impact of changes in minimum enlistment standards on academic attrition for MOS with medium complexity/validity or greater. For some MOS, especially those with low difficulty or low complexity/validity, reducing or reaching a desired level of academic attrition may be best achieved by methods other than adjustments in minimum enlistment standards.

Second, school sample size (N), on which academic attrition estimates are based, can significantly impact the quality of the decisions made based on these estimates. Operationally, this has implications about *whether* to and *how much* to adjust enlistment standards to achieve desired objectives. A cost-benefit analysis indicated that a sufficiently large sample size allows

smaller changes in minimum enlistment standards in order to achieve a targeted attrition rate with high confidence, which in turn translates to potential savings in terms of the size of the eligible applicant pool. Specifically, we observed that larger sample size ($N > 400$) is more likely to produce more accurate estimates and thereby, better quality decisions.

Third, personnel management and training decisions could be greatly improved in some cases by incorporating information other than cognitive aptitude. For example, as evident from our results, for some MOS, understanding the effects of enlistment standards on attrition may not be especially informative for determining what strategy is best for minimizing attrition. Therefore, school proponents of those MOS may be interested in understanding the effects on attrition from adjusting enlistment standards (e.g., educational requirements) other than cognitive aptitude. In particular, MOS with low difficulty or low complexity/validity could benefit from extending the current model with this additional information.

There are a number of practical recommendations for performing and interpreting this analysis that would aid operational decisions. We presented these recommendations and suggested several areas for future research that could greatly extend the proposed approach. Research in these suggested areas would further enhance the effectiveness of the difficult, but strategically important, decisions Army managers must make.

REFERENCES

Barrick, M.R., & Mount, M.K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, *44*, 1-26.

Barrick, M.R., Mount, M.K., & Judge, T.A. (2001). Personality and performance at the beginning of the new millennium: What do we know and where do we go next. *International Journal of Selection & Assessment*, *9*, 9-30.

Boyes, J.W., Hoffman, D.L., & Low, S.A. (1989). An econometric analysis of the bank credit scoring problem. *Journal of Econometrics*, *40*, 3-14.

Bobko, P., Roth, P.L., & Potosky, D. (1999). Derivation and implications of a meta-analysis matrix incorporating cognitive ability, alternative predictors, and job performance. *Personnel Psychology*, *52*, 561-589.

Cannon-Bowers, J.A., Salas, E., Tannenbaum, S.I., & Mathieu, J.E. (1995). Toward theoretically based principles of training effectiveness: A model and initial empirical investigation. *Military Psychology*, *7*, 141-164.

Carretta, T.R., & Ree, M.J. (2000). General and specific cognitive and psychomotor abilities in personnel selection: The prediction of training and job performance. *International Journal of Selection & Assessment*, *8*, 227-236.

Cohen, J., Cohen, P., West, S.G., & Aiken, L.S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Diaz,T., Ingerick,M, & Lightfoot,M. (2004). *Replication of Zeidner, Johnson, and Colleagues' Method for Estimating Army Aptitude (AA) Composites* (ARI Study Report, in preparation). Arlington, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Earles, J.A., & Ree, M.J. (1992). The predictive validity of the ASVAB for training grades. *Educational & Psychological Measurement*, *52*, 721-725.

Eden, D., & Ravid, G. (1982). Pygmalion versus self-expectancy: Effects of instructor- and self-expectancy on trainee performance. *Organizational Behavior and Human Performance*, *30*, 351-364.

Gist, M.E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology*, *74*, 884-891.

Greene, W.H. (1997). *Econometric analysis* (3rd ed.). Upper Saddle River, NJ: Prentice-Hall.

Greenston, P.M. (2002). *Proposed New Army Aptitude Area Composites: A Summary of Research Results* (SR 2002 – 03). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Guion, R.M. (1998). *Assessment, measurement, and prediction for personnel decisions*. Mahwah, NJ: Lawrence Erlbaum Associates.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica, 47*, 153-161.

Hough, L.M., & Furnham, A. (2003). Use of personality variables in work settings. In W.C. Borman, D.R. Ilgen, & R.J. Klimoski (Eds.), *Handbook of psychology: Industrial and organizational psychology* (Vol. 12, pp. 131-169). New York: John Wiley & Sons.

Hough, L.M., Oswald, F.L., & Ployhart, R.E. (2001). Determinants, detection and amelioration of adverse impact in personnel selection procedures: Issues, evidence and lessons learned. *International Journal of Selection & Assessment, 9*, 152-194.

Hunter, J.E., & Hunter, R.F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96*, 72-98.

Hunter, J.E., & Schmidt, F.L. (1990). *Methods of meta-analysis: Correcting error and bias in research findings*. Newbury Park, CA: Sage Publications.

Johnson, C.D., Zeidner, C.D., & Leaman, J.A. (1992). *Improving classification efficiency by restructuring Army job families* (TR-947). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Judge, T.A., & Ilies, R. (2002). Relationship of personality to performance motivation: A meta-analytic review. *Journal of Applied Psychology, 87*, 797-807.

Larson, G.E., Booth-Kewley, S., & Ryan, M.A.K. (2002). Predictors of Navy attrition: II. A demonstration of potential usefulness for screening. *Military Medicine, 167*, 770-776.

Laurence, J.H. (1984). *Education standards for military enlistment and the search for successful recruits* (FR-PRD-84-4). Alexandria, VA: Human Resources Research Organization.

Laurence, J.H. (1987). *Military enlistment policy and education credentials: Evaluation and improvement* (FR-PRD-87-33). Alexandria, VA: Human Resources Research Organization.

Laurence, J.H., Naughton, J., & Harris, D.A. (1995). *Attrition revisited: Identifying the problem and its solutions* (FR-PRD-95-01). Alexandria, VA: Human Resources Research Organization.

Martocchio, J.J. (1994). Effects of conceptions of ability on anxiety, self-efficacy and learning in training. *Journal of Applied Psychology, 79*, 819-825.

Mathieu, J.E., Martineau, J., & Tannenbaum, S.I. (1993). Individual and situational influences on the development of self-efficacy: Implications for training effectiveness. *Personnel Psychology*, *46*, 125-147.

McCullagh, P., & Nelder, J. (1983). *Generalized linear models*. New York, NY: Chapman and Hall.

McHenry, J.J., Hough, L.M., Toquam, J.L., Hanson, M., & Ashworth, S. (1990). Project A validity results: The relationship between predictor and criterion domains. *Personnel Psychology*, *43*, 335-354.

Olea, M.M., & Ree, M.J. (1994). Predicting pilot and navigator criteria: Not much more than g. *Journal of Applied Psychology*, *79*, 845-851.

Ree, M.J., & Carretta, T.R. (1999). Lack of ability is not always the problem. *Journal of Business & Psychology*, *14*, 165-171.

Ree, M.J., Carretta, T.R., & Teachout, M.S. (1995). Role of ability and prior knowledge in complex training performance. *Journal of Applied Psychology*, *80*, 721-730.

Ree, M.J., & Earles, J.A. (1991). Predicting training success: Not much more than g. *Personnel Psychology*, *44*, 321-332.

Roth, P.L. (1994). Missing data: A conceptual review for applied psychologists. *Personnel Psychology*, *47*, 537-560.

Sackett, P.R., & Roth, L. (1996). Multi-stage selection strategies: A Monte Carlo investigation of effects on performance and minority hiring. *Personnel Psychology*, *49*, 549-572.

Sackett, P.R., Schmitt, N., Ellingson, J.E., & Kabin, M.B. (2001). High-stakes testing in employment, credentialing, and higher education: Prospects in a post-affirmative-action world. *American Psychologist*, *56*, 302-318.

Salas, E., & Cannon-Bowers, J.A. (2001). The science of training: A decade of progress. *Annual Review of Psychology*, *52*, 471-499.

Schmidt, F.L., & Hunter, J.E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin*, *124*, 262-274.

Schmitt, N., & Chan, D. (1998). *Personnel selection: A theoretical approach*. Thousand Oaks, CA: Sage Publications.

Schmitt, N., Rogers, W., Chan, D., Sheppard, L., & Jennings, D. (1997). Adverse impact and predictive efficiency of various predictor combinations. *Journal of Applied Psychology*, *82*, 719-730.

Scholarios, D., Johnson, C.D., & Zeidner, J. (1994). Selecting predictors for maximizing the classification efficiency of a battery. *Journal of Applied Psychology*, *79*, 412-424.

Statman, M.A. (1993). *Improving the effectiveness of employment testing through classification: Alternative methods of developing test composites for optimal job assignment and vocational counseling*. Unpublished doctoral dissertation.

Switzer, F.S., & Roth, P.L. (2002). Coping with missing data. In S.G. Rogelberg (Ed.), *Handbook of research methods in industrial and organizational psychology* (pp. 310-323). Malden, MA: Blackwell Publishers.

Tabachnick, B.G., & Fidell, L.S. (1996). *Using multivariate statistics* (3rd ed.). New York: HarperCollins Publishers.

U.S. Department of Defense (1990). *Conversion tables: Armed Services Vocational Aptitude Battery (ASVAB) Forms 8-19* (DOD 1304.12W1). Washington, DC: U.S. Department of Defense.

U.S. General Accounting Office (1997). *Military attrition: DoD could save millions by better screening enlisted personnel* (GAO/NSIAD-97-39). Washington, DC: U.S. General Accounting Office.

U.S. General Accounting Office (1998). *Military attrition: DoD needs to better analyze reasons for separation and improve recruiting systems* (GAO/NSIAD-98-117). Washington, DC: U.S. General Accounting Office.

U.S. General Accounting Office (2000). *Military attrition: First-term recruiting and attrition continue to require focused attention* (GAO/NSIAD-00-102). Washington, DC: U.S. General Accounting Office.

Zeidner, J., Johnson, C.D., & Scholarios, D. (1997). Evaluating military selection and classification systems in the multiple job context. *Military Psychology*, *9*, 169-186.

Zeidner, J., Johnson, C.D., Vladimirsky, Y., & Weldon, S. (2000). *Specifications for an operational two-tiered classification system for the Army, Vol. 1* (TR-1108-VOL-1). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

APPENDIX A: NOTES ON SIMULATING AA COMPOSITE AND TRAINING PERFORMANCE DATA

Notes on Simulating AA Composite and Training Performance Data

Converting Old AA to New AA Scores

Note that conversion of old AA scores is only an issue if the original scores on the nine ASVAB subtests are no longer available. If original scores for the ASVAB subtests are otherwise unavailable, conversion from old to new AA scores can be carried out using the matrix expression

$$\underline{X}_{new} = U_{new}\left[DU_{old}^{-1}\left(\underline{X}_{old} + \underline{K}_{old}\right)\right] - \underline{K}_{new}$$

In the expression above, $\underline{X}_{old}$ is the vector of nine old AA scores; $\underline{X}_{new}$ is the vector of nine new AA scores; U_{old} is the 9x9 matrix whose rows are the vectors of conversion weights and $\underline{K}_{old}$ is a 9x1 vector of constants for the old unit weighted AA score; U_{new} is the 9x7 matrix whose rows are the vectors of conversion weights and $\underline{K}_{new}$ is a 9x1 vector of constants for the new AA composites; finally D is the 7x9 matrix constructed by deleting the rows in the 9x9 identity matrix corresponding to Numerical Operation (NO) and Coding Speed (CS) subtests.[13] Note that the expression inside the parentheses is just the vector of seven ASVAB subtests (with NO and CS dropped).

Conceptually, this formula is essentially de-standardizing the old unit-weighted AA (standard) scores to the original sum of ASVAB subtest scores, then applying the new conversion weights and constants to those scores to obtain the new AA (standard) scores currently in operational use by the Army (Zeidner et al., 2000). To verify the accuracy of this procedure and of the conversion weights for moving from the old unit-weighted AA standard cores to the sum of ASVAB subtest scores, we did the following.

First, we obtained historical information for converting the sum of ASVAB subtest scores to the old unit-weighted AA standard scores (U.S. Department of Defense, 1990). Second, we regressed unit-weighted AA scores, excluding the lowest and highest possible values of 40 and 160, onto their respective sum of ASVAB subtest scores (based on the conversion information) for all 9 AA composites.[14] The resulting regression parameters (intercepts, regression weights) represented the conversion weights and constants (e.g., U_{old} and K_{old}) for converting from the old unit-weighted AA standard scores to the sum of ASVAB subtest scores for all 9 AA composites. These values are reported in Table 1 (at end of Appendix A). For convenience, Table 2 contains the conversion weights (U_{new}) and constants (K_{new}) for generating the new AA standard scores.

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[13] For example, if NO and CS correspond to the third and fourth subtests in X_{old} then delete the third and fourth rows in the 9x9 identity matrix to obtain the 7x9 matrix *D*.

[14] We excluded 40 and 160 as these values reflect the minimum and maximum conversion values for converting ASVAB subtest scores to unit-weighted AA scores, and effectively represent all AA scores below or above 40 and 160 respectively.

Third, upon having generated the conversion weights, we validated the weights by comparing the predicted AA standard score (using the previously generated regression parameters) to the corresponding AA standard score from which the predicted scores were based. Across all 9 composites, only 7 cases exhibited residuals greater than 0.5. Of these 7 cases, the difference between the tabulated AA scores and AA scores estimated using our procedure, rounded to the nearest integer, was no greater than 1.0. In summary, for the purposes of estimating attrition rates, there is strong support for the accuracy of our procedure and of the obtained conversion weights and constants (see Table 1) for converting old unit-weighted AA standard scores to new AA standard scores.

Procedure for Generating Synthetic AA and Training Performance Data

When simulating AA composite and training performance data, our ultimate goal was to generate synthetic data consistent with training requirements and testing process of the typical MOS. In brief, the testing process in the typical MOS school can be characterized as a multiple hurdle system. Students are required to pass each test in the sequence before they can move on to the next test. Passing a test means obtaining a grade that is equal to or better than the minimum passing grade for the test, which could (and does) vary from one test to another. Generally, a student who fails a given test is allowed one opportunity to retrain and retake the test. Therefore, according to Army policy, students have at most two attempts to pass each test in the sequence. If they fail a test in a sequence (i.e., scoring below the passing grade on the second attempt), then the student is dropped from the class.[15]

To model these features we did the following. Let T be equal to the total number of tests that trainees must pass to successfully complete the training. Using i and j to respectively index the trainee and test, the vector of test scores for the ith trainee is represented by $\{Y_{i1}, Y_{i2}, \ldots, Y_{iT}\}$. The relationship between the test score Y_{ij} *on one attempt* and the AA score X_i is assumed to be given by regression

$$Y_{ij} = a_j + b_j X_i + \varepsilon_{ij}$$

Conditional on the AA score X_i, the regression errors ε_{ij} are assumed to be independent across trainee given the jth test, but are correlated across tests for a particular trainee. That is, $cor(\varepsilon_{ij}, \varepsilon_{i'j'})$ equals zero if $i \neq i'$ for any j and j', but is possibly non-zero for $i = i'$.

The above specification completely describes the mean and covariance structure of the test scores indicative of trainee performance. The overall structure of the multivariate outcome variable of test scores conditional on the AA score can be described in terms of the regression parameters, the intercept and coefficient (a_j,b_j), validities $r_j = cor(Y_{ij}, X_j)$ and intra-person error correlation $cor(\varepsilon_{ij}, \varepsilon_{i'j'})$. The different operational scenarios used in our simulation experiments represent different combinations of these three sets of parameters. In our simulation, we

[15] When dropped from a class, the student may be recycled into the same MOS school, an alternative MOS school, or discharged from the Army.

included trainee re-test behavior (from being allowed two attempts to pass a test), by assuming that the two attempts for given applicant are independent.[16]

[16] Given that retraining of applicants who failed the first attempt likely is designed to give them a better chance of passing the second attempt, the assumption of independence between two attempts would tend to lead to slightly more conservative attrition estimates. Note that estimation of the between-attempts correlation would require test scores from both attempts. Adequate sample size may be difficult to achieve for this purpose.

Table 1
Conversion Weights (U_{old}) and Constants (K_{old}) for Converting Unit-Weighted AA Standard Scores to ASVAB Subtest Scores

AA	K_{old}	U_{old}								
		GS	AR	AS	NO	CS	MK	MC	EI	VE
CL	9.867458061	0	0.7327769188	0	0	0	0.7327769188	0	0	0.7327769188
CO	25.77762373	0	0.6291526689	0.6291526689	0	0.6291526689	0	0.6291526689	0	0
EL	13.03000728	0.5655765767	0.5655765767	0	0	0	0.5655765767	0	0.5655765767	0
FA	20.55727062	0	0.6029386374	0	0	0.6029386374	0.6029386374	0.6029386374	0	0
GM	16.94413156	0.5851640076	0	0.5851640076	0	0	0.5851640076	0	0.5851640076	0
MM	22.01437581	0	0	0.6101231611	0.6101231611	0	0	0.6101231611	0.6101231611	0
OF	24.01570681	0	0	0.6201570681	0.6201570681	0	0	0.6201570681	0	0.6201570681
SC	17.44052664	0	0.5874735691	0.5874735691	0	0	0	0.5874735691	0	0.5874735691
ST	14.72794969	0.5740020673	0	0	0	0	0.5740020673	0.5740020673	0	0.5740020673

Note. To maintain consistency with Zeidner et al. (2000), the sign of reported K_{old} values have been reversed from the original computed values.

Table 2
Conversion Weights (U_{new}) and Constants (K_{new}) for Converting ASVAB Subtest Scores to New AA Standard Scores

AA	K_{new}	U_{new}						
		GS	AR	AS	MK	MC	EI	VE
CL	12.85471	0	0.72448	0.07998	0.55550	0.10706	0.07994	0.71014
CO	19.18658	0.18428	0.31335	0.43199	0.58940	0.35082	0.20235	0.31154
EL	18.72901	0.07647	0.41509	0.38240	0.45180	0.23783	0.30353	0.50746
FA	18.71933	0.14019	0.40246	0.37852	0.56254	0.39385	0.16691	0.32991
GM	18.98138	0.21608	0.43480	0.52538	0.41700	0.26436	0.30311	0.21889
MM	18.15045	0.05343	0.30138	0.88831	0.25702	0.35001	0.30237	0.21049
OF	18.95577	0.13160	0.50414	0.52394	0.31436	0.33310	0.19771	0.37426
SC	17.81739	0.01142	0.40419	0.25777	0.58996	0.22784	0.32507	0.54009
ST	17.09884	0.12016	0.46735	0.22971	0.44773	0.28646	0.14781	0.64276

Source: Zeidner et al. (2000)

APPENDIX B: TABLES

Table 1. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.48	0.078	0.49	0.057	0.49	0.041	0.49	0.029	0.49	0.020	0.49	0.015
GM= 81	0.48	0.077	0.48	0.057	0.48	0.040	0.48	0.029	0.48	0.020	0.48	0.014
GM= 82	0.47	0.076	0.48	0.056	0.48	0.040	0.48	0.028	0.48	0.020	0.48	0.014
GM= 83	0.47	0.075	0.47	0.055	0.48	0.039	0.47	0.028	0.47	0.019	0.47	0.014
GM= 84	0.47	0.074	0.47	0.054	0.47	0.039	0.47	0.028	0.47	0.019	0.47	0.014
GM= 85	0.46	0.073	0.46	0.053	0.47	0.038	0.46	0.027	0.46	0.019	0.46	0.013
GM= 86	0.46	0.071	0.46	0.052	0.46	0.037	0.46	0.027	0.46	0.018	0.46	0.013
GM= 87	0.45	0.070	0.45	0.051	0.45	0.037	0.45	0.026	0.45	0.018	0.45	0.013
GM= 88	0.45	0.068	0.45	0.050	0.45	0.036	0.45	0.025	0.45	0.018	0.45	0.013
GM= 89	0.44	0.067	0.44	0.049	0.44	0.035	0.44	0.025	0.44	0.017	0.44	0.012
GM= 90	0.43	0.065	0.44	0.048	0.44	0.034	0.43	0.024	0.43	0.017	0.43	0.012
GM= 91	0.43	0.064	0.43	0.046	0.43	0.033	0.43	0.024	0.43	0.016	0.43	0.012
GM= 92	0.42	0.062	0.42	0.045	0.42	0.033	0.42	0.023	0.42	0.016	0.42	0.011
GM= 93	0.41	0.061	0.42	0.044	0.42	0.032	0.41	0.022	0.42	0.016	0.42	0.011
GM= 94	0.41	0.059	0.41	0.042	0.41	0.031	0.41	0.022	0.41	0.015	0.41	0.011
GM= 95	0.40	0.057	0.40	0.041	0.40	0.030	0.40	0.021	0.40	0.015	0.40	0.010
GM= 96	0.39	0.056	0.39	0.040	0.40	0.029	0.39	0.020	0.39	0.014	0.39	0.010
GM= 97	0.39	0.054	0.39	0.039	0.39	0.028	0.39	0.020	0.39	0.014	0.39	0.010
GM= 98	0.38	0.052	0.38	0.037	0.38	0.027	0.38	0.019	0.38	0.013	0.38	0.009
GM= 99	0.37	0.051	0.37	0.036	0.37	0.027	0.37	0.018	0.37	0.013	0.37	0.009
GM=100	0.36	0.050	0.36	0.035	0.37	0.026	0.36	0.018	0.36	0.012	0.36	0.009
GM=101	0.36	0.049	0.36	0.034	0.36	0.025	0.36	0.017	0.36	0.012	0.36	0.009
GM=102	0.35	0.048	0.35	0.033	0.35	0.025	0.35	0.017	0.35	0.012	0.35	0.008
GM=103	0.34	0.047	0.34	0.033	0.34	0.024	0.34	0.016	0.34	0.012	0.34	0.008
GM=104	0.33	0.046	0.33	0.032	0.33	0.024	0.33	0.016	0.33	0.011	0.33	0.008
GM=105	0.33	0.046	0.33	0.032	0.33	0.024	0.32	0.016	0.32	0.011	0.32	0.008
GM=106	0.32	0.046	0.32	0.032	0.32	0.023	0.32	0.016	0.32	0.011	0.32	0.008
GM=107	0.31	0.046	0.31	0.032	0.31	0.023	0.31	0.016	0.31	0.011	0.31	0.008
GM=108	0.30	0.046	0.30	0.032	0.30	0.024	0.30	0.016	0.30	0.011	0.30	0.008
GM=109	0.29	0.047	0.29	0.032	0.29	0.024	0.29	0.016	0.29	0.011	0.29	0.008

Table 1. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.29	0.048	0.28	0.033	0.28	0.024	0.28	0.016	0.28	0.012	0.28	0.008
GM=111	0.28	0.049	0.28	0.034	0.28	0.025	0.28	0.016	0.28	0.012	0.28	0.008
GM=112	0.27	0.050	0.27	0.034	0.27	0.025	0.27	0.017	0.27	0.012	0.27	0.008
GM=113	0.26	0.051	0.26	0.035	0.26	0.026	0.26	0.017	0.26	0.012	0.26	0.009
GM=114	0.25	0.053	0.25	0.036	0.25	0.026	0.25	0.018	0.25	0.013	0.25	0.009
GM=115	0.25	0.054	0.25	0.037	0.25	0.027	0.25	0.018	0.25	0.013	0.24	0.009
GM=116	0.24	0.056	0.24	0.038	0.24	0.027	0.24	0.019	0.24	0.013	0.24	0.009
GM=117	0.23	0.057	0.23	0.040	0.23	0.028	0.23	0.019	0.23	0.014	0.23	0.009
GM=118	0.23	0.058	0.22	0.041	0.22	0.029	0.22	0.020	0.22	0.014	0.22	0.010
GM=119	0.22	0.060	0.22	0.042	0.22	0.029	0.22	0.020	0.22	0.014	0.21	0.010
GM=120	0.21	0.061	0.21	0.043	0.21	0.030	0.21	0.021	0.21	0.015	0.21	0.010

Table 2. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.19	0.108	0.18	0.080	0.18	0.058	0.17	0.043	0.17	0.031	0.17	0.023
GM= 81	0.18	0.105	0.17	0.078	0.17	0.056	0.17	0.041	0.17	0.030	0.17	0.022
GM= 82	0.18	0.102	0.17	0.075	0.16	0.054	0.16	0.040	0.16	0.028	0.16	0.021
GM= 83	0.17	0.098	0.16	0.072	0.16	0.052	0.16	0.038	0.16	0.027	0.15	0.020
GM= 84	0.17	0.095	0.16	0.069	0.15	0.050	0.15	0.036	0.15	0.026	0.15	0.019
GM= 85	0.16	0.091	0.15	0.066	0.15	0.047	0.15	0.034	0.15	0.025	0.14	0.018
GM= 86	0.15	0.087	0.15	0.063	0.14	0.045	0.14	0.033	0.14	0.023	0.14	0.017
GM= 87	0.15	0.083	0.14	0.060	0.14	0.042	0.13	0.031	0.13	0.022	0.13	0.016
GM= 88	0.14	0.079	0.13	0.056	0.13	0.040	0.13	0.029	0.13	0.020	0.13	0.015
GM= 89	0.14	0.075	0.13	0.053	0.13	0.037	0.12	0.027	0.12	0.019	0.12	0.014
GM= 90	0.13	0.070	0.12	0.050	0.12	0.035	0.12	0.025	0.12	0.018	0.12	0.013
GM= 91	0.12	0.066	0.12	0.046	0.11	0.032	0.11	0.023	0.11	0.016	0.11	0.012
GM= 92	0.12	0.061	0.11	0.043	0.11	0.030	0.11	0.022	0.11	0.015	0.11	0.011
GM= 93	0.11	0.057	0.11	0.040	0.10	0.028	0.10	0.020	0.10	0.014	0.10	0.010
GM= 94	0.10	0.052	0.10	0.037	0.10	0.025	0.10	0.018	0.10	0.013	0.10	0.009
GM= 95	0.10	0.048	0.09	0.034	0.09	0.023	0.09	0.017	0.09	0.012	0.09	0.009
GM= 96	0.09	0.044	0.09	0.031	0.09	0.021	0.09	0.015	0.09	0.011	0.09	0.008
GM= 97	0.09	0.040	0.08	0.028	0.08	0.019	0.08	0.014	0.08	0.010	0.08	0.007
GM= 98	0.08	0.036	0.08	0.026	0.08	0.018	0.08	0.013	0.08	0.009	0.08	0.007
GM= 99	0.08	0.033	0.07	0.024	0.07	0.016	0.07	0.012	0.07	0.008	0.07	0.006
GM=100	0.07	0.030	0.07	0.022	0.07	0.015	0.07	0.011	0.07	0.007	0.07	0.005
GM=101	0.07	0.028	0.07	0.020	0.07	0.014	0.07	0.010	0.07	0.007	0.07	0.005
GM=102	0.06	0.026	0.06	0.019	0.06	0.013	0.06	0.009	0.06	0.006	0.06	0.005
GM=103	0.06	0.024	0.06	0.018	0.06	0.012	0.06	0.008	0.06	0.006	0.06	0.004
GM=104	0.05	0.023	0.05	0.017	0.05	0.011	0.05	0.008	0.05	0.006	0.05	0.004
GM=105	0.05	0.022	0.05	0.016	0.05	0.011	0.05	0.007	0.05	0.005	0.05	0.004
GM=106	0.05	0.022	0.05	0.015	0.05	0.010	0.05	0.007	0.05	0.005	0.05	0.004
GM=107	0.04	0.021	0.04	0.015	0.04	0.010	0.04	0.007	0.04	0.005	0.04	0.004
GM=108	0.04	0.021	0.04	0.014	0.04	0.010	0.04	0.007	0.04	0.005	0.04	0.004
GM=109	0.04	0.020	0.04	0.014	0.04	0.009	0.04	0.007	0.04	0.005	0.04	0.004

Table 2. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.04	0.020	0.04	0.014	0.04	0.009	0.04	0.007	0.04	0.005	0.04	0.003
GM=111	0.03	0.020	0.03	0.014	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=112	0.03	0.020	0.03	0.014	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=113	0.03	0.020	0.03	0.013	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=114	0.03	0.020	0.03	0.013	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=115	0.03	0.021	0.03	0.013	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=116	0.03	0.021	0.03	0.013	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003
GM=117	0.03	0.021	0.02	0.013	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003
GM=118	0.02	0.022	0.02	0.013	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003
GM=119	0.02	0.022	0.02	0.013	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003
GM=120	0.02	0.022	0.02	0.013	0.02	0.008	0.02	0.006	0.02	0.004	0.02	0.003

Table 3. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.23	0.117	0.20	0.096	0.20	0.074	0.19	0.052	0.19	0.037	0.19	0.027
GM= 81	0.22	0.114	0.19	0.094	0.19	0.072	0.18	0.051	0.18	0.036	0.18	0.027
GM= 82	0.22	0.112	0.19	0.091	0.18	0.070	0.17	0.050	0.17	0.035	0.17	0.026
GM= 83	0.21	0.109	0.18	0.088	0.17	0.068	0.16	0.048	0.16	0.034	0.16	0.025
GM= 84	0.20	0.106	0.17	0.085	0.16	0.065	0.15	0.046	0.15	0.033	0.15	0.024
GM= 85	0.19	0.102	0.16	0.082	0.15	0.062	0.14	0.044	0.14	0.031	0.14	0.023
GM= 86	0.18	0.099	0.15	0.078	0.14	0.059	0.13	0.041	0.13	0.029	0.13	0.022
GM= 87	0.16	0.094	0.14	0.074	0.13	0.055	0.12	0.039	0.12	0.027	0.12	0.020
GM= 88	0.15	0.090	0.12	0.069	0.12	0.052	0.11	0.036	0.11	0.025	0.11	0.019
GM= 89	0.14	0.085	0.11	0.064	0.11	0.048	0.10	0.033	0.10	0.023	0.10	0.017
GM= 90	0.13	0.080	0.10	0.059	0.09	0.043	0.09	0.030	0.09	0.021	0.09	0.015
GM= 91	0.12	0.074	0.09	0.054	0.08	0.039	0.08	0.027	0.08	0.019	0.08	0.014
GM= 92	0.11	0.069	0.08	0.049	0.07	0.034	0.07	0.023	0.07	0.016	0.07	0.012
GM= 93	0.09	0.063	0.07	0.043	0.07	0.030	0.06	0.020	0.06	0.014	0.06	0.010
GM= 94	0.08	0.056	0.06	0.038	0.06	0.026	0.05	0.018	0.05	0.012	0.05	0.009
GM= 95	0.07	0.050	0.05	0.033	0.05	0.022	0.05	0.015	0.05	0.010	0.05	0.008
GM= 96	0.06	0.043	0.05	0.028	0.04	0.019	0.04	0.013	0.04	0.009	0.04	0.006
GM= 97	0.05	0.037	0.04	0.024	0.04	0.016	0.04	0.011	0.04	0.008	0.04	0.005
GM= 98	0.04	0.031	0.03	0.020	0.03	0.013	0.03	0.009	0.03	0.006	0.03	0.005
GM= 99	0.03	0.026	0.03	0.016	0.03	0.011	0.03	0.008	0.03	0.005	0.03	0.004
GM=100	0.03	0.021	0.02	0.014	0.02	0.009	0.02	0.006	0.02	0.005	0.02	0.003
GM=101	0.02	0.018	0.02	0.012	0.02	0.008	0.02	0.006	0.02	0.004	0.02	0.003
GM=102	0.02	0.014	0.02	0.010	0.02	0.007	0.02	0.005	0.02	0.003	0.02	0.002
GM=103	0.02	0.012	0.01	0.008	0.01	0.006	0.01	0.004	0.01	0.003	0.01	0.002
GM=104	0.01	0.010	0.01	0.007	0.01	0.005	0.01	0.004	0.01	0.003	0.01	0.002
GM=105	0.01	0.009	0.01	0.006	0.01	0.005	0.01	0.003	0.01	0.002	0.01	0.002
GM=106	0.01	0.008	0.01	0.006	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.002
GM=107	0.01	0.007	0.01	0.005	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.001
GM=108	0.01	0.007	0.01	0.005	0.01	0.003	0.01	0.002	0.01	0.002	0.01	0.001
GM=109	0.01	0.006	0.01	0.004	0.00	0.003	0.00	0.002	0.00	0.002	0.00	0.001

Table 3. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Low Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.01	0.006	0.00	0.004	0.00	0.003	0.00	0.002	0.00	0.001	0.00	0.001
GM=111	0.00	0.005	0.00	0.003	0.00	0.002	0.00	0.002	0.00	0.001	0.00	0.001
GM=112	0.00	0.005	0.00	0.003	0.00	0.002	0.00	0.002	0.00	0.001	0.00	0.001
GM=113	0.00	0.005	0.00	0.003	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001
GM=114	0.00	0.005	0.00	0.003	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001
GM=115	0.00	0.005	0.00	0.002	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001
GM=116	0.00	0.005	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001	0.00	0.000
GM=117	0.00	0.005	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001	0.00	0.000
GM=118	0.00	0.005	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.001	0.00	0.000
GM=119	0.00	0.005	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.000	0.00	0.000
GM=120	0.00	0.005	0.00	0.002	0.00	0.001	0.00	0.001	0.00	0.000	0.00	0.000

Table 4. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.54	0.072	0.55	0.051	0.55	0.037	0.55	0.026	0.55	0.018	0.55	0.013
GM= 81	0.54	0.071	0.54	0.051	0.54	0.037	0.54	0.026	0.54	0.018	0.54	0.013
GM= 82	0.53	0.070	0.54	0.050	0.54	0.036	0.54	0.025	0.54	0.018	0.54	0.013
GM= 83	0.53	0.070	0.53	0.050	0.53	0.036	0.53	0.025	0.53	0.018	0.53	0.013
GM= 84	0.52	0.069	0.53	0.049	0.53	0.036	0.53	0.025	0.53	0.017	0.53	0.013
GM= 85	0.52	0.068	0.52	0.049	0.52	0.035	0.52	0.024	0.52	0.017	0.52	0.012
GM= 86	0.51	0.067	0.52	0.048	0.52	0.035	0.52	0.024	0.52	0.017	0.52	0.012
GM= 87	0.51	0.066	0.51	0.047	0.51	0.034	0.51	0.024	0.51	0.017	0.51	0.012
GM= 88	0.50	0.065	0.51	0.046	0.51	0.034	0.50	0.023	0.50	0.016	0.50	0.012
GM= 89	0.50	0.064	0.50	0.046	0.50	0.033	0.50	0.023	0.50	0.016	0.50	0.012
GM= 90	0.49	0.062	0.49	0.045	0.49	0.033	0.49	0.023	0.49	0.016	0.49	0.011
GM= 91	0.48	0.061	0.49	0.044	0.49	0.032	0.48	0.022	0.48	0.016	0.48	0.011
GM= 92	0.48	0.060	0.48	0.043	0.48	0.031	0.48	0.022	0.48	0.015	0.48	0.011
GM= 93	0.47	0.058	0.47	0.042	0.47	0.031	0.47	0.021	0.47	0.015	0.47	0.011
GM= 94	0.46	0.057	0.46	0.041	0.46	0.030	0.46	0.021	0.46	0.015	0.46	0.010
GM= 95	0.46	0.056	0.46	0.040	0.46	0.029	0.45	0.020	0.46	0.014	0.45	0.010
GM= 96	0.45	0.054	0.45	0.039	0.45	0.029	0.45	0.020	0.45	0.014	0.45	0.010
GM= 97	0.44	0.053	0.44	0.038	0.44	0.028	0.44	0.019	0.44	0.013	0.44	0.009
GM= 98	0.43	0.052	0.43	0.037	0.43	0.027	0.43	0.018	0.43	0.013	0.43	0.009
GM= 99	0.42	0.051	0.42	0.036	0.42	0.027	0.42	0.018	0.42	0.013	0.42	0.009
GM=100	0.42	0.050	0.41	0.035	0.41	0.026	0.41	0.018	0.41	0.012	0.41	0.009
GM=101	0.41	0.049	0.41	0.035	0.41	0.025	0.40	0.017	0.40	0.012	0.40	0.008
GM=102	0.40	0.048	0.40	0.034	0.40	0.025	0.40	0.017	0.40	0.012	0.40	0.008
GM=103	0.39	0.047	0.39	0.034	0.39	0.025	0.39	0.016	0.39	0.012	0.39	0.008
GM=104	0.38	0.047	0.38	0.033	0.38	0.024	0.38	0.016	0.38	0.012	0.38	0.008
GM=105	0.37	0.047	0.37	0.033	0.37	0.024	0.37	0.016	0.37	0.012	0.37	0.008
GM=106	0.36	0.047	0.36	0.033	0.36	0.024	0.36	0.016	0.36	0.012	0.36	0.008
GM=107	0.35	0.047	0.35	0.033	0.35	0.024	0.35	0.016	0.35	0.012	0.35	0.008
GM=108	0.34	0.047	0.34	0.033	0.34	0.024	0.34	0.016	0.34	0.012	0.34	0.008
GM=109	0.33	0.048	0.33	0.034	0.33	0.024	0.33	0.016	0.33	0.012	0.33	0.008

Table 4. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.32	0.049	0.32	0.034	0.32	0.025	0.32	0.016	0.32	0.012	0.32	0.008
GM=111	0.31	0.050	0.31	0.035	0.31	0.025	0.31	0.017	0.31	0.012	0.31	0.008
GM=112	0.30	0.052	0.30	0.036	0.30	0.026	0.30	0.017	0.30	0.013	0.30	0.008
GM=113	0.30	0.053	0.29	0.037	0.29	0.026	0.29	0.018	0.29	0.013	0.29	0.009
GM=114	0.29	0.054	0.28	0.038	0.28	0.027	0.28	0.018	0.28	0.013	0.28	0.009
GM=115	0.28	0.056	0.28	0.039	0.28	0.028	0.28	0.018	0.28	0.014	0.28	0.009
GM=116	0.27	0.058	0.27	0.040	0.27	0.028	0.27	0.019	0.27	0.014	0.27	0.009
GM=117	0.26	0.059	0.26	0.041	0.26	0.029	0.26	0.019	0.26	0.014	0.26	0.010
GM=118	0.25	0.061	0.25	0.042	0.25	0.030	0.25	0.020	0.25	0.015	0.25	0.010
GM=119	0.24	0.062	0.24	0.043	0.24	0.030	0.24	0.021	0.24	0.015	0.24	0.010
GM=120	0.23	0.064	0.23	0.044	0.23	0.031	0.23	0.021	0.23	0.015	0.23	0.010

Table 5. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.30	0.099	0.31	0.073	0.30	0.052	0.30	0.038	0.31	0.026	0.31	0.019
GM= 81	0.30	0.097	0.30	0.072	0.30	0.051	0.30	0.037	0.30	0.026	0.30	0.019
GM= 82	0.29	0.095	0.30	0.070	0.29	0.050	0.29	0.036	0.29	0.025	0.29	0.018
GM= 83	0.28	0.093	0.29	0.069	0.29	0.049	0.28	0.035	0.29	0.025	0.29	0.018
GM= 84	0.28	0.091	0.28	0.067	0.28	0.047	0.28	0.034	0.28	0.024	0.28	0.017
GM= 85	0.27	0.088	0.27	0.065	0.27	0.046	0.27	0.033	0.27	0.023	0.27	0.017
GM= 86	0.26	0.085	0.27	0.063	0.26	0.045	0.26	0.032	0.26	0.023	0.26	0.016
GM= 87	0.26	0.083	0.26	0.061	0.26	0.043	0.26	0.031	0.26	0.022	0.26	0.016
GM= 88	0.25	0.080	0.25	0.059	0.25	0.041	0.25	0.030	0.25	0.021	0.25	0.015
GM= 89	0.24	0.077	0.24	0.056	0.24	0.040	0.24	0.029	0.24	0.020	0.24	0.014
GM= 90	0.23	0.073	0.24	0.054	0.23	0.038	0.23	0.027	0.23	0.019	0.23	0.014
GM= 91	0.23	0.070	0.23	0.051	0.22	0.036	0.22	0.026	0.23	0.018	0.23	0.013
GM= 92	0.22	0.067	0.22	0.049	0.22	0.034	0.22	0.025	0.22	0.017	0.22	0.012
GM= 93	0.21	0.063	0.21	0.046	0.21	0.032	0.21	0.023	0.21	0.016	0.21	0.012
GM= 94	0.20	0.060	0.20	0.044	0.20	0.030	0.20	0.022	0.20	0.015	0.20	0.011
GM= 95	0.19	0.056	0.19	0.041	0.19	0.029	0.19	0.021	0.19	0.014	0.19	0.010
GM= 96	0.19	0.053	0.19	0.038	0.18	0.027	0.18	0.019	0.18	0.013	0.18	0.010
GM= 97	0.18	0.050	0.18	0.036	0.18	0.025	0.18	0.018	0.18	0.013	0.18	0.009
GM= 98	0.17	0.047	0.17	0.034	0.17	0.023	0.17	0.017	0.17	0.012	0.17	0.008
GM= 99	0.16	0.044	0.16	0.031	0.16	0.022	0.16	0.016	0.16	0.011	0.16	0.008
GM=100	0.15	0.041	0.15	0.029	0.15	0.020	0.15	0.015	0.15	0.010	0.15	0.007
GM=101	0.15	0.038	0.15	0.027	0.14	0.019	0.15	0.014	0.15	0.010	0.15	0.007
GM=102	0.14	0.036	0.14	0.026	0.14	0.018	0.14	0.013	0.14	0.009	0.14	0.006
GM=103	0.13	0.034	0.13	0.024	0.13	0.017	0.13	0.012	0.13	0.008	0.13	0.006
GM=104	0.12	0.032	0.12	0.023	0.12	0.016	0.12	0.011	0.12	0.008	0.12	0.006
GM=105	0.12	0.031	0.12	0.022	0.12	0.016	0.12	0.011	0.12	0.008	0.12	0.006
GM=106	0.11	0.030	0.11	0.022	0.11	0.015	0.11	0.010	0.11	0.007	0.11	0.005
GM=107	0.10	0.029	0.10	0.021	0.10	0.015	0.10	0.010	0.10	0.007	0.10	0.005
GM=108	0.10	0.029	0.10	0.021	0.10	0.014	0.10	0.010	0.10	0.007	0.10	0.005

Table 5. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=109	0.09	0.029	0.09	0.020	0.09	0.014	0.09	0.010	0.09	0.007	0.09	0.005
GM=110	0.09	0.028	0.09	0.020	0.09	0.014	0.09	0.010	0.09	0.007	0.09	0.005
GM=111	0.08	0.028	0.08	0.020	0.08	0.014	0.08	0.010	0.08	0.007	0.08	0.005
GM=112	0.08	0.028	0.08	0.020	0.08	0.014	0.08	0.009	0.08	0.007	0.08	0.005
GM=113	0.07	0.028	0.07	0.020	0.07	0.014	0.07	0.009	0.07	0.007	0.07	0.005
GM=114	0.07	0.028	0.07	0.020	0.07	0.014	0.07	0.009	0.07	0.007	0.07	0.005
GM=115	0.06	0.028	0.06	0.020	0.06	0.014	0.06	0.009	0.06	0.007	0.06	0.005
GM=116	0.06	0.029	0.06	0.020	0.06	0.014	0.06	0.009	0.06	0.007	0.06	0.005
GM=117	0.06	0.029	0.06	0.020	0.06	0.014	0.06	0.009	0.06	0.007	0.06	0.005
GM=118	0.05	0.029	0.05	0.019	0.05	0.013	0.05	0.009	0.05	0.007	0.05	0.005
GM=119	0.05	0.029	0.05	0.019	0.05	0.013	0.05	0.009	0.05	0.007	0.05	0.005
GM=120	0.05	0.029	0.05	0.019	0.05	0.013	0.05	0.009	0.05	0.006	0.05	0.005

Table 6. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.30	0.108	0.29	0.080	0.30	0.055	0.30	0.039	0.30	0.027	0.30	0.019
GM= 81	0.29	0.106	0.28	0.079	0.29	0.055	0.29	0.039	0.29	0.027	0.29	0.019
GM= 82	0.28	0.105	0.28	0.078	0.28	0.054	0.28	0.039	0.28	0.027	0.28	0.019
GM= 83	0.27	0.103	0.27	0.077	0.27	0.054	0.27	0.038	0.27	0.026	0.27	0.019
GM= 84	0.26	0.101	0.26	0.076	0.26	0.053	0.25	0.038	0.26	0.026	0.26	0.019
GM= 85	0.25	0.099	0.24	0.074	0.25	0.052	0.24	0.037	0.25	0.026	0.25	0.018
GM= 86	0.24	0.096	0.23	0.072	0.23	0.050	0.23	0.036	0.23	0.025	0.23	0.018
GM= 87	0.23	0.093	0.22	0.070	0.22	0.049	0.22	0.035	0.22	0.024	0.22	0.018
GM= 88	0.22	0.090	0.21	0.067	0.21	0.047	0.21	0.034	0.21	0.024	0.21	0.017
GM= 89	0.21	0.087	0.20	0.064	0.20	0.045	0.19	0.032	0.20	0.023	0.20	0.016
GM= 90	0.19	0.083	0.18	0.061	0.18	0.043	0.18	0.031	0.18	0.021	0.18	0.015
GM= 91	0.18	0.079	0.17	0.058	0.17	0.041	0.17	0.029	0.17	0.020	0.17	0.015
GM= 92	0.17	0.075	0.16	0.054	0.16	0.038	0.16	0.027	0.16	0.019	0.16	0.014
GM= 93	0.15	0.070	0.15	0.051	0.14	0.035	0.14	0.025	0.14	0.018	0.14	0.013
GM= 94	0.14	0.065	0.13	0.047	0.13	0.032	0.13	0.023	0.13	0.016	0.13	0.011
GM= 95	0.13	0.060	0.12	0.042	0.12	0.029	0.12	0.021	0.12	0.015	0.12	0.010
GM= 96	0.11	0.054	0.11	0.038	0.11	0.026	0.11	0.019	0.11	0.013	0.11	0.009
GM= 97	0.10	0.049	0.10	0.034	0.10	0.023	0.10	0.017	0.10	0.012	0.10	0.008
GM= 98	0.09	0.044	0.09	0.030	0.09	0.021	0.08	0.015	0.09	0.010	0.09	0.007
GM= 99	0.08	0.039	0.08	0.027	0.08	0.018	0.08	0.013	0.08	0.009	0.08	0.006
GM=100	0.07	0.034	0.07	0.023	0.07	0.016	0.07	0.011	0.07	0.008	0.07	0.006
GM=101	0.06	0.030	0.06	0.021	0.06	0.014	0.06	0.010	0.06	0.007	0.06	0.005
GM=102	0.05	0.026	0.05	0.018	0.05	0.012	0.05	0.009	0.05	0.006	0.05	0.004
GM=103	0.04	0.023	0.04	0.016	0.04	0.011	0.04	0.008	0.04	0.006	0.04	0.004
GM=104	0.04	0.020	0.04	0.014	0.04	0.010	0.04	0.007	0.04	0.005	0.04	0.003
GM=105	0.03	0.018	0.03	0.013	0.03	0.009	0.03	0.006	0.03	0.005	0.03	0.003
GM=106	0.03	0.016	0.03	0.011	0.03	0.008	0.03	0.006	0.03	0.004	0.03	0.003
GM=107	0.02	0.015	0.02	0.010	0.02	0.007	0.02	0.005	0.03	0.004	0.03	0.003
GM=108	0.02	0.013	0.02	0.010	0.02	0.007	0.02	0.005	0.02	0.003	0.02	0.002
GM=109	0.02	0.012	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003	0.02	0.002

Table 6. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for Medium Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.02	0.011	0.02	0.008	0.02	0.006	0.02	0.004	0.02	0.003	0.02	0.002
GM=111	0.01	0.010	0.01	0.007	0.01	0.005	0.01	0.004	0.01	0.003	0.01	0.002
GM=112	0.01	0.009	0.01	0.007	0.01	0.005	0.01	0.003	0.01	0.002	0.01	0.002
GM=113	0.01	0.008	0.01	0.006	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.002
GM=114	0.01	0.008	0.01	0.006	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.001
GM=115	0.01	0.007	0.01	0.005	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.001
GM=116	0.01	0.007	0.01	0.005	0.01	0.003	0.01	0.002	0.01	0.002	0.01	0.001
GM=117	0.01	0.006	0.01	0.004	0.01	0.003	0.01	0.002	0.01	0.001	0.01	0.001
GM=118	0.01	0.006	0.01	0.004	0.00	0.003	0.00	0.002	0.00	0.001	0.00	0.001
GM=119	0.00	0.006	0.00	0.004	0.00	0.002	0.00	0.002	0.00	0.001	0.00	0.001
GM=120	0.00	0.005	0.00	0.003	0.00	0.002	0.00	0.002	0.00	0.001	0.00	0.001

Table 7. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.66	0.058	0.66	0.040	0.67	0.029	0.66	0.020	0.66	0.014	0.66	0.010
GM= 81	0.66	0.057	0.66	0.040	0.66	0.029	0.66	0.020	0.66	0.014	0.66	0.010
GM= 82	0.65	0.057	0.65	0.040	0.66	0.029	0.66	0.020	0.66	0.014	0.66	0.010
GM= 83	0.65	0.057	0.65	0.039	0.65	0.029	0.65	0.020	0.65	0.014	0.65	0.010
GM= 84	0.64	0.056	0.65	0.039	0.65	0.029	0.65	0.020	0.65	0.014	0.65	0.010
GM= 85	0.64	0.056	0.64	0.039	0.64	0.029	0.64	0.020	0.64	0.014	0.64	0.010
GM= 86	0.63	0.055	0.64	0.039	0.64	0.029	0.64	0.020	0.64	0.014	0.64	0.010
GM= 87	0.63	0.055	0.63	0.038	0.63	0.028	0.63	0.020	0.63	0.014	0.63	0.010
GM= 88	0.62	0.055	0.63	0.038	0.63	0.028	0.63	0.019	0.63	0.014	0.63	0.010
GM= 89	0.62	0.054	0.62	0.038	0.62	0.028	0.62	0.019	0.62	0.014	0.62	0.010
GM= 90	0.61	0.053	0.62	0.037	0.62	0.028	0.62	0.019	0.62	0.013	0.62	0.010
GM= 91	0.61	0.053	0.61	0.037	0.61	0.027	0.61	0.019	0.61	0.013	0.61	0.009
GM= 92	0.60	0.052	0.60	0.037	0.61	0.027	0.60	0.019	0.60	0.013	0.60	0.009
GM= 93	0.60	0.052	0.60	0.036	0.60	0.027	0.60	0.018	0.60	0.013	0.60	0.009
GM= 94	0.59	0.051	0.59	0.036	0.59	0.027	0.59	0.018	0.59	0.013	0.59	0.009
GM= 95	0.58	0.050	0.58	0.036	0.59	0.026	0.58	0.018	0.58	0.013	0.58	0.009
GM= 96	0.58	0.050	0.58	0.035	0.58	0.026	0.58	0.018	0.58	0.012	0.58	0.009
GM= 97	0.57	0.049	0.57	0.035	0.57	0.026	0.57	0.017	0.57	0.012	0.57	0.009
GM= 98	0.56	0.049	0.56	0.034	0.56	0.025	0.56	0.017	0.56	0.012	0.56	0.009
GM= 99	0.55	0.048	0.55	0.034	0.55	0.025	0.55	0.017	0.55	0.012	0.55	0.009
GM=100	0.54	0.048	0.54	0.034	0.55	0.025	0.54	0.017	0.54	0.012	0.54	0.008
GM=101	0.54	0.048	0.54	0.034	0.54	0.025	0.54	0.017	0.54	0.012	0.54	0.008
GM=102	0.53	0.048	0.53	0.034	0.53	0.024	0.53	0.017	0.53	0.012	0.53	0.008
GM=103	0.52	0.048	0.52	0.034	0.52	0.024	0.52	0.016	0.52	0.012	0.52	0.008
GM=104	0.51	0.048	0.51	0.034	0.51	0.024	0.51	0.016	0.51	0.012	0.51	0.008
GM=105	0.50	0.048	0.50	0.034	0.50	0.024	0.50	0.016	0.50	0.012	0.50	0.008
GM=106	0.49	0.049	0.49	0.034	0.49	0.025	0.49	0.017	0.49	0.012	0.49	0.008
GM=107	0.48	0.050	0.48	0.035	0.48	0.025	0.48	0.017	0.48	0.012	0.48	0.008
GM=108	0.47	0.051	0.47	0.035	0.47	0.025	0.47	0.017	0.47	0.012	0.47	0.009
GM=109	0.46	0.052	0.46	0.036	0.46	0.026	0.46	0.017	0.46	0.012	0.46	0.009

Table 7. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, Low Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.45	0.053	0.45	0.037	0.45	0.026	0.45	0.018	0.45	0.013	0.45	0.009
GM=111	0.44	0.055	0.44	0.038	0.44	0.027	0.44	0.018	0.44	0.013	0.44	0.009
GM=112	0.43	0.057	0.43	0.039	0.43	0.028	0.43	0.019	0.43	0.013	0.43	0.009
GM=113	0.42	0.059	0.42	0.040	0.42	0.029	0.42	0.020	0.42	0.014	0.42	0.010
GM=114	0.41	0.061	0.41	0.042	0.41	0.030	0.41	0.020	0.41	0.014	0.41	0.010
GM=115	0.40	0.063	0.40	0.043	0.40	0.031	0.39	0.021	0.40	0.015	0.39	0.011
GM=116	0.39	0.066	0.38	0.044	0.38	0.032	0.38	0.022	0.38	0.015	0.38	0.011
GM=117	0.38	0.068	0.37	0.046	0.37	0.033	0.37	0.023	0.37	0.016	0.37	0.011
GM=118	0.37	0.070	0.36	0.048	0.36	0.034	0.36	0.023	0.36	0.017	0.36	0.012
GM=119	0.35	0.073	0.35	0.049	0.35	0.035	0.35	0.024	0.35	0.017	0.35	0.012
GM=120	0.34	0.075	0.34	0.051	0.34	0.036	0.34	0.025	0.34	0.018	0.34	0.013

Table 8. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.47	0.078	0.47	0.055	0.48	0.039	0.47	0.027	0.48	0.019	0.48	0.014
GM= 81	0.46	0.077	0.47	0.054	0.47	0.039	0.47	0.027	0.47	0.019	0.47	0.014
GM= 82	0.46	0.076	0.46	0.054	0.46	0.039	0.46	0.027	0.46	0.019	0.46	0.014
GM= 83	0.45	0.075	0.46	0.053	0.46	0.038	0.45	0.027	0.46	0.019	0.46	0.013
GM= 84	0.44	0.075	0.45	0.053	0.45	0.038	0.45	0.026	0.45	0.019	0.45	0.013
GM= 85	0.44	0.074	0.44	0.052	0.44	0.037	0.44	0.026	0.44	0.019	0.44	0.013
GM= 86	0.43	0.072	0.43	0.051	0.43	0.037	0.43	0.026	0.43	0.018	0.43	0.013
GM= 87	0.42	0.071	0.43	0.051	0.43	0.036	0.42	0.025	0.43	0.018	0.43	0.013
GM= 88	0.41	0.070	0.42	0.050	0.42	0.036	0.42	0.025	0.42	0.018	0.42	0.013
GM= 89	0.41	0.068	0.41	0.049	0.41	0.035	0.41	0.024	0.41	0.017	0.41	0.012
GM= 90	0.40	0.067	0.40	0.048	0.40	0.034	0.40	0.024	0.40	0.017	0.40	0.012
GM= 91	0.39	0.065	0.39	0.046	0.39	0.033	0.39	0.023	0.39	0.017	0.39	0.012
GM= 92	0.38	0.063	0.38	0.045	0.38	0.033	0.38	0.023	0.38	0.016	0.38	0.011
GM= 93	0.37	0.062	0.37	0.044	0.37	0.032	0.37	0.022	0.37	0.016	0.37	0.011
GM= 94	0.36	0.060	0.36	0.043	0.36	0.031	0.36	0.021	0.36	0.015	0.36	0.011
GM= 95	0.35	0.058	0.35	0.041	0.35	0.030	0.35	0.020	0.35	0.015	0.35	0.010
GM= 96	0.34	0.056	0.34	0.040	0.34	0.029	0.34	0.020	0.34	0.014	0.34	0.010
GM= 97	0.33	0.054	0.33	0.038	0.33	0.028	0.33	0.019	0.33	0.014	0.33	0.010
GM= 98	0.32	0.052	0.32	0.037	0.32	0.027	0.32	0.018	0.32	0.013	0.32	0.009
GM= 99	0.31	0.050	0.31	0.035	0.31	0.026	0.31	0.018	0.31	0.012	0.31	0.009
GM=100	0.30	0.048	0.30	0.034	0.30	0.025	0.30	0.017	0.30	0.012	0.30	0.009
GM=101	0.29	0.046	0.29	0.033	0.29	0.024	0.28	0.016	0.29	0.011	0.29	0.008
GM=102	0.27	0.044	0.27	0.032	0.27	0.023	0.27	0.015	0.27	0.011	0.27	0.008
GM=103	0.26	0.043	0.26	0.031	0.26	0.022	0.26	0.015	0.26	0.011	0.26	0.008
GM=104	0.25	0.042	0.25	0.030	0.25	0.022	0.25	0.014	0.25	0.010	0.25	0.007
GM=105	0.24	0.041	0.24	0.029	0.24	0.021	0.24	0.014	0.24	0.010	0.24	0.007
GM=106	0.23	0.040	0.23	0.028	0.23	0.021	0.23	0.014	0.23	0.010	0.23	0.007
GM=107	0.22	0.039	0.22	0.028	0.22	0.020	0.22	0.013	0.22	0.010	0.22	0.007
GM=108	0.21	0.039	0.21	0.028	0.21	0.020	0.21	0.013	0.21	0.010	0.21	0.007
GM=109	0.20	0.039	0.20	0.028	0.20	0.020	0.20	0.013	0.20	0.010	0.20	0.007

Table 8. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, Medium Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.19	0.039	0.19	0.028	0.19	0.020	0.19	0.013	0.19	0.010	0.19	0.007
GM=111	0.18	0.039	0.18	0.028	0.18	0.020	0.18	0.013	0.18	0.010	0.18	0.007
GM=112	0.17	0.040	0.17	0.028	0.17	0.020	0.17	0.013	0.17	0.010	0.17	0.007
GM=113	0.16	0.040	0.16	0.028	0.16	0.020	0.16	0.013	0.16	0.010	0.16	0.007
GM=114	0.15	0.041	0.15	0.028	0.15	0.020	0.15	0.014	0.15	0.010	0.15	0.007
GM=115	0.14	0.041	0.14	0.029	0.14	0.020	0.14	0.014	0.14	0.010	0.14	0.007
GM=116	0.14	0.041	0.13	0.029	0.13	0.021	0.13	0.014	0.13	0.010	0.13	0.007
GM=117	0.13	0.042	0.13	0.029	0.13	0.021	0.13	0.014	0.13	0.010	0.13	0.007
GM=118	0.12	0.042	0.12	0.029	0.12	0.021	0.12	0.014	0.12	0.010	0.12	0.007
GM=119	0.11	0.042	0.11	0.029	0.11	0.021	0.11	0.014	0.11	0.010	0.11	0.007
GM=120	0.11	0.042	0.11	0.029	0.11	0.021	0.11	0.014	0.11	0.010	0.10	0.007

Table 9. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM= 80	0.42	0.080	0.43	0.055	0.43	0.037	0.43	0.026	0.43	0.019	0.43	0.013
GM= 81	0.41	0.080	0.42	0.055	0.42	0.038	0.42	0.026	0.42	0.019	0.42	0.013
GM= 82	0.40	0.079	0.41	0.055	0.41	0.038	0.41	0.026	0.41	0.019	0.41	0.013
GM= 83	0.39	0.079	0.40	0.055	0.40	0.038	0.40	0.027	0.40	0.019	0.40	0.013
GM= 84	0.38	0.079	0.39	0.055	0.39	0.038	0.39	0.027	0.39	0.019	0.39	0.013
GM= 85	0.37	0.078	0.38	0.055	0.38	0.038	0.38	0.027	0.38	0.019	0.38	0.013
GM= 86	0.36	0.077	0.37	0.054	0.37	0.038	0.37	0.027	0.37	0.019	0.37	0.013
GM= 87	0.35	0.076	0.36	0.054	0.36	0.038	0.36	0.026	0.36	0.019	0.36	0.013
GM= 88	0.34	0.075	0.35	0.053	0.35	0.037	0.35	0.026	0.35	0.019	0.35	0.013
GM= 89	0.33	0.074	0.33	0.053	0.33	0.037	0.33	0.026	0.33	0.019	0.33	0.013
GM= 90	0.32	0.073	0.32	0.052	0.32	0.036	0.32	0.026	0.32	0.018	0.32	0.013
GM= 91	0.30	0.071	0.31	0.051	0.31	0.036	0.31	0.025	0.31	0.018	0.31	0.013
GM= 92	0.29	0.069	0.29	0.049	0.29	0.035	0.29	0.025	0.29	0.017	0.29	0.012
GM= 93	0.27	0.067	0.28	0.048	0.28	0.034	0.28	0.024	0.28	0.017	0.28	0.012
GM= 94	0.26	0.064	0.26	0.046	0.26	0.032	0.26	0.023	0.26	0.016	0.26	0.011
GM= 95	0.24	0.061	0.25	0.044	0.25	0.031	0.24	0.022	0.25	0.016	0.25	0.011
GM= 96	0.23	0.058	0.23	0.042	0.23	0.030	0.23	0.021	0.23	0.015	0.23	0.010
GM= 97	0.21	0.055	0.22	0.040	0.21	0.028	0.21	0.020	0.21	0.014	0.21	0.010
GM= 98	0.20	0.052	0.20	0.037	0.20	0.026	0.20	0.019	0.20	0.013	0.20	0.009
GM= 99	0.18	0.048	0.18	0.035	0.18	0.024	0.18	0.017	0.18	0.012	0.18	0.009
GM=100	0.17	0.044	0.17	0.032	0.17	0.023	0.17	0.016	0.17	0.011	0.17	0.008
GM=101	0.15	0.041	0.15	0.030	0.15	0.021	0.15	0.015	0.15	0.010	0.15	0.007
GM=102	0.14	0.037	0.14	0.027	0.14	0.019	0.14	0.014	0.14	0.009	0.14	0.007
GM=103	0.12	0.034	0.13	0.025	0.12	0.017	0.12	0.013	0.13	0.009	0.13	0.006
GM=104	0.11	0.032	0.11	0.023	0.11	0.016	0.11	0.012	0.11	0.008	0.11	0.006
GM=105	0.10	0.029	0.10	0.021	0.10	0.015	0.10	0.011	0.10	0.007	0.10	0.005
GM=106	0.09	0.027	0.09	0.019	0.09	0.014	0.09	0.010	0.09	0.007	0.09	0.005
GM=107	0.08	0.025	0.08	0.018	0.08	0.013	0.08	0.009	0.08	0.006	0.08	0.005
GM=108	0.07	0.024	0.07	0.017	0.07	0.012	0.07	0.009	0.07	0.006	0.07	0.004
GM=109	0.06	0.022	0.06	0.016	0.06	0.011	0.06	0.008	0.06	0.005	0.06	0.004

Table 9. Average (AVG) Attrition Rates and Standard Errors (STD) by Cut Score and N for High Difficulty, High Complexity Condition

Cut Scores	Alternative Sample Sizes											
	N = 100		N = 200		N = 400		N = 800		N = 1600		N = 3200	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
GM=110	0.05	0.021	0.05	0.015	0.05	0.011	0.05	0.008	0.05	0.005	0.05	0.004
GM=111	0.05	0.020	0.05	0.014	0.05	0.010	0.05	0.007	0.05	0.005	0.05	0.004
GM=112	0.04	0.018	0.04	0.013	0.04	0.009	0.04	0.007	0.04	0.005	0.04	0.003
GM=113	0.04	0.017	0.04	0.012	0.04	0.009	0.04	0.006	0.04	0.004	0.04	0.003
GM=114	0.03	0.016	0.03	0.012	0.03	0.008	0.03	0.006	0.03	0.004	0.03	0.003
GM=115	0.03	0.015	0.03	0.011	0.03	0.008	0.03	0.005	0.03	0.004	0.03	0.003
GM=116	0.02	0.014	0.02	0.010	0.02	0.007	0.02	0.005	0.02	0.003	0.02	0.003
GM=117	0.02	0.013	0.02	0.009	0.02	0.007	0.02	0.005	0.02	0.003	0.02	0.002
GM=118	0.02	0.013	0.02	0.009	0.02	0.006	0.02	0.004	0.02	0.003	0.02	0.002
GM=119	0.02	0.012	0.02	0.008	0.02	0.006	0.02	0.004	0.02	0.003	0.02	0.002
GM=120	0.01	0.011	0.01	0.008	0.01	0.005	0.01	0.004	0.01	0.003	0.01	0.002

APPENDIX C: FIGURES

Average Attrition Rates by Cut Score and Sample Size (N)

Figure 1. Results for Low Difficulty, Low Complexity Condition
Attrition Rates by Cut Score and N

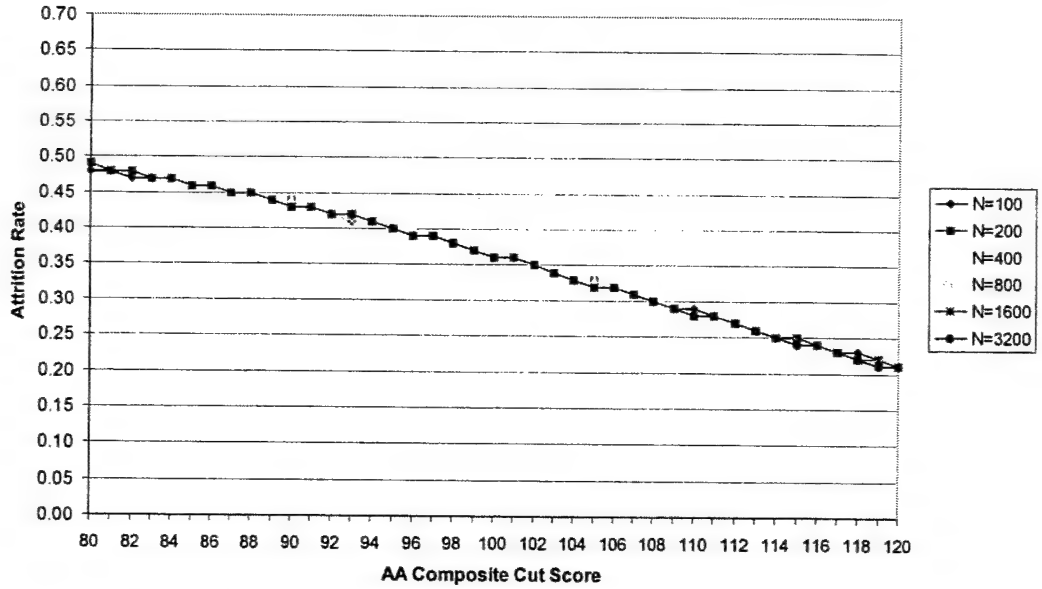
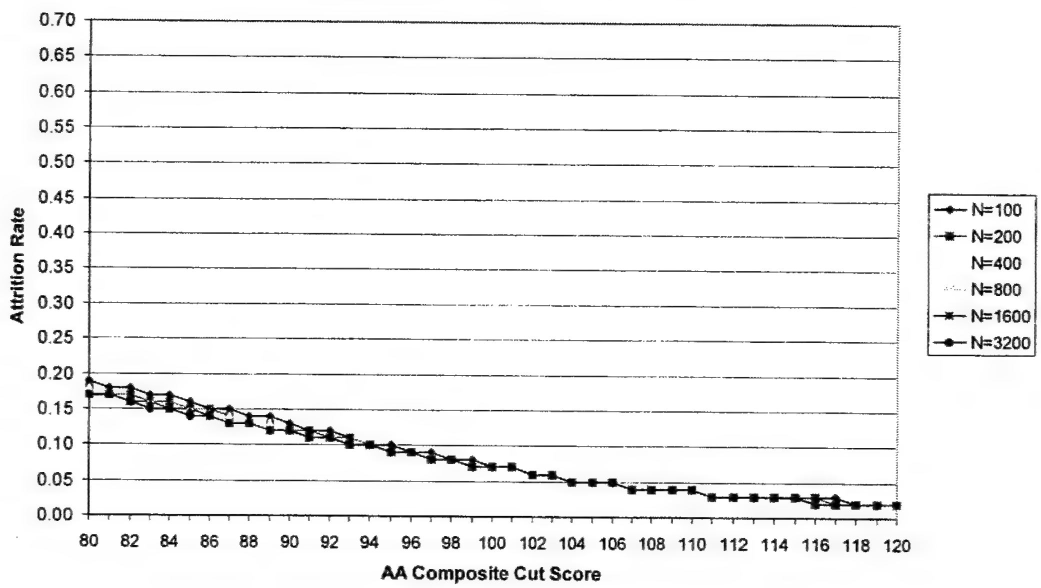


Figure 2. Results for Low Difficulty, Medium Complexity Condition
Attrition Rates by Cut Score and N



Average Attrition Rates by Cut Score and Sample Size (N)

Figure 3. Results for Low Difficulty, High Complexity Condition
Attrition Rates by Cut Score and N

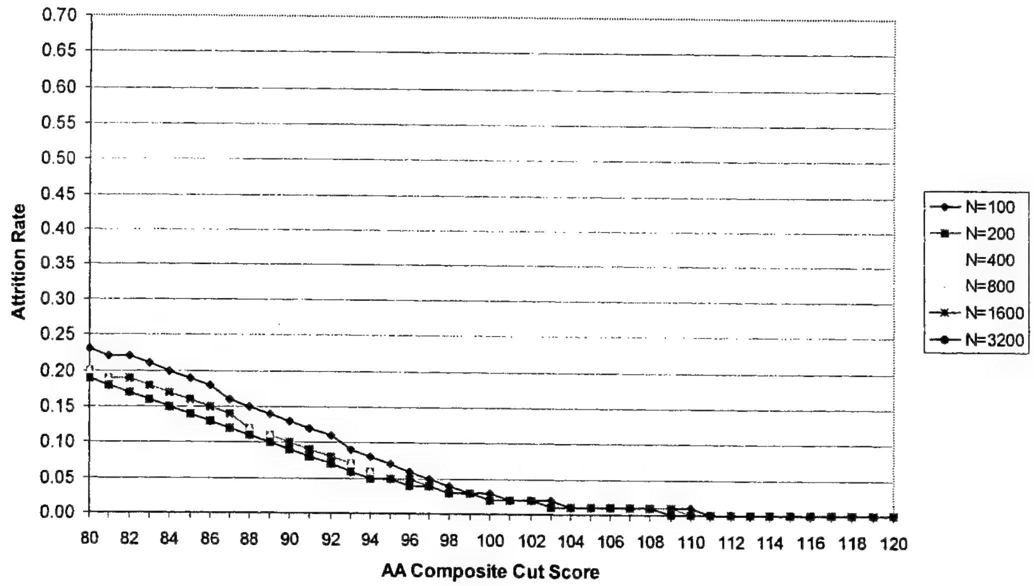
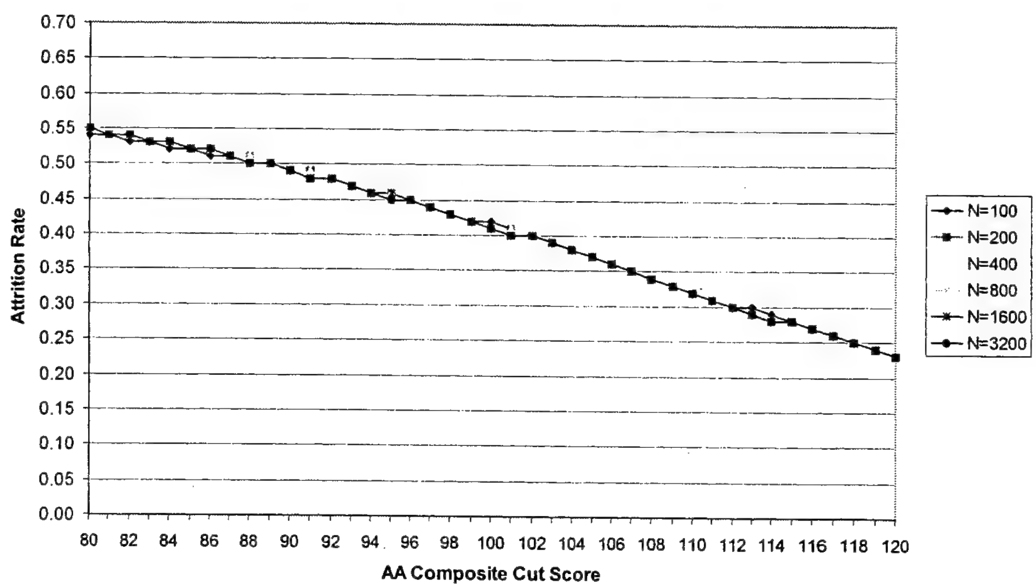


Figure 4. Results for Medium Difficulty, Low Complexity Condition
Attrition Rates by Cut Score and N



Average Attrition Rates by Cut Score and Sample Size (N)

Figure 5. Results for Medium Difficulty, Medium Complexity Condition
Attrition Rates by Cut Score and N

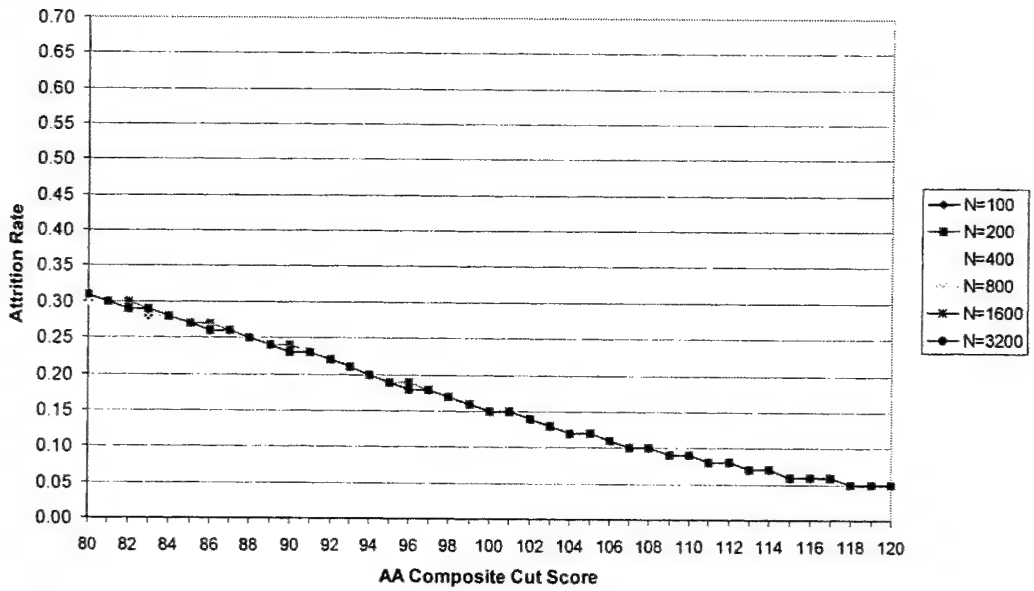
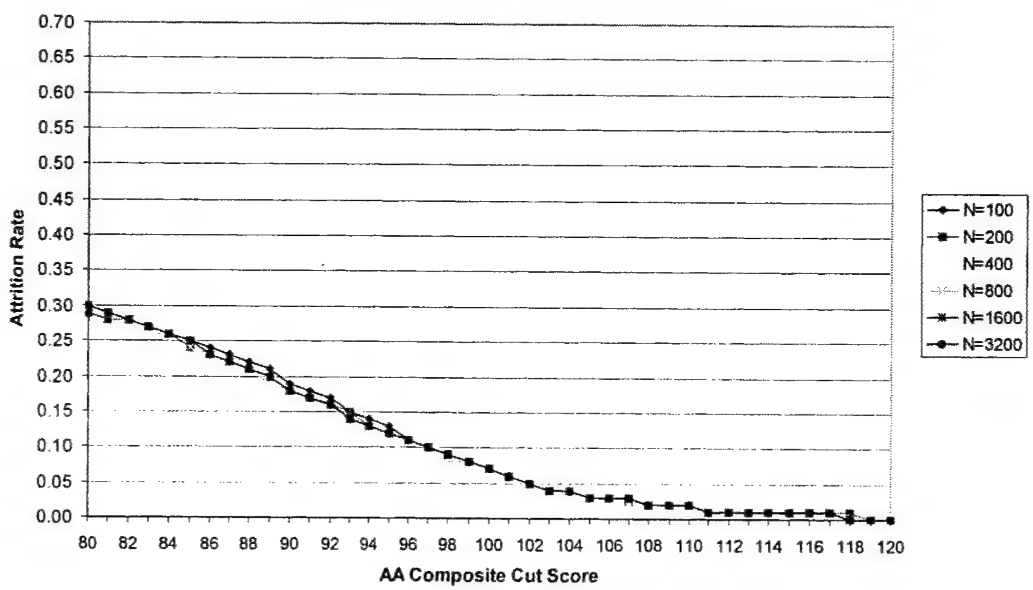


Figure 6. Results for Medium Difficulty, High Complexity Condition
Attrition Rates by Cut Score and N



Average Attrition Rates by Cut Score and Sample Size (N)

**Figure 7. Results for High Difficulty, Low Complexity Condition
Attrition Rates by Cut Score and N**

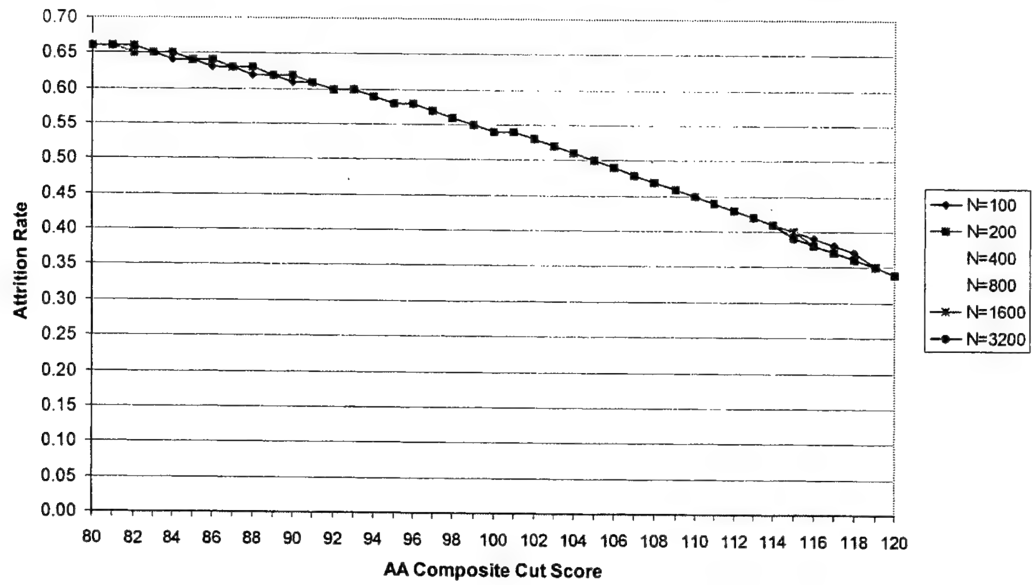
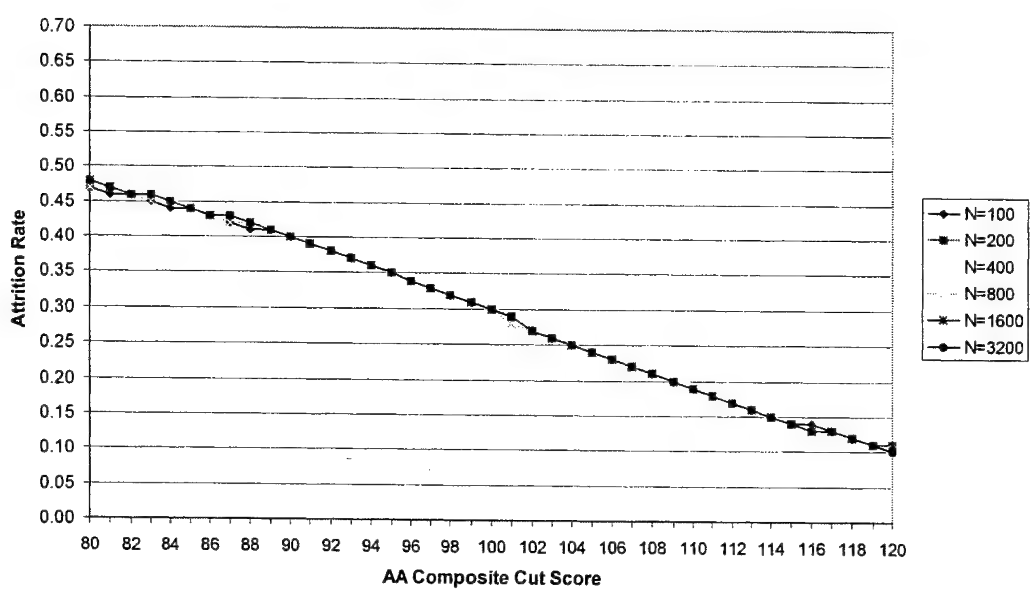
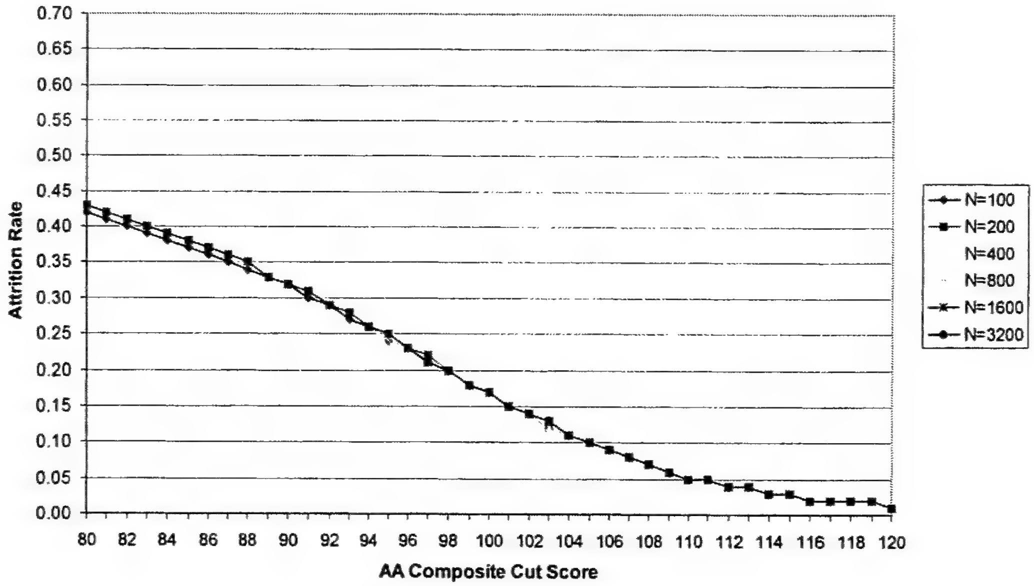


**Figure 8. Results for High Difficulty, Medium Complexity Condition
Attrition Rates by Cut Score and N**

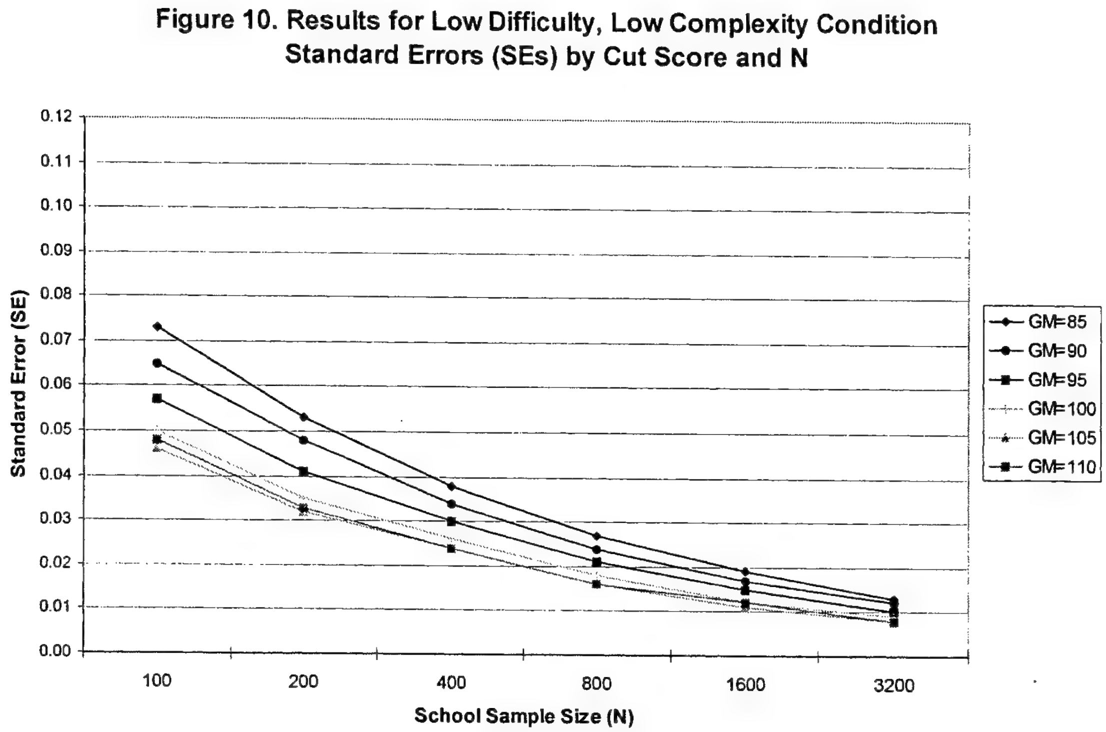


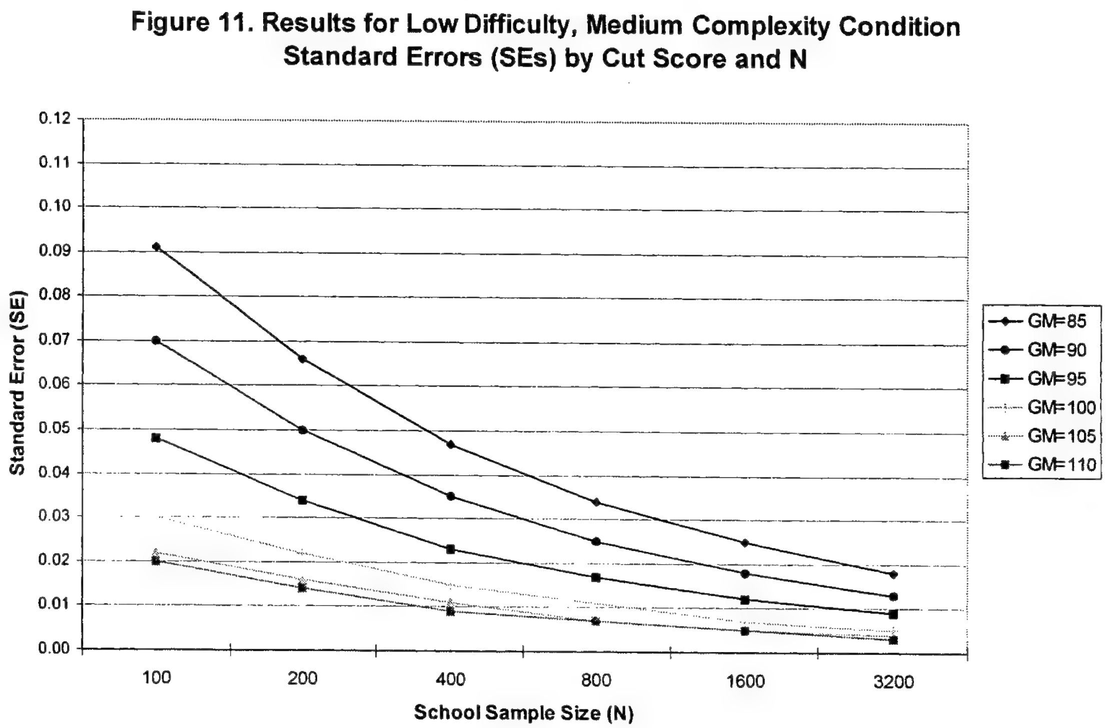
Average Attrition Rates by Cut Score and Sample Size (N)

Figure 9. Results for High Difficulty, High Complexity Condition
Attrition Rates by Cut Score and N



Standard Errors (SEs) by Cut Score and Sample Size (N)





Standard Errors (SEs) by Cut Score and Sample Size (N)

Figure 12. Results for Low Difficulty, High Complexity Condition
Standard Errors (SEs) by Cut Score and N

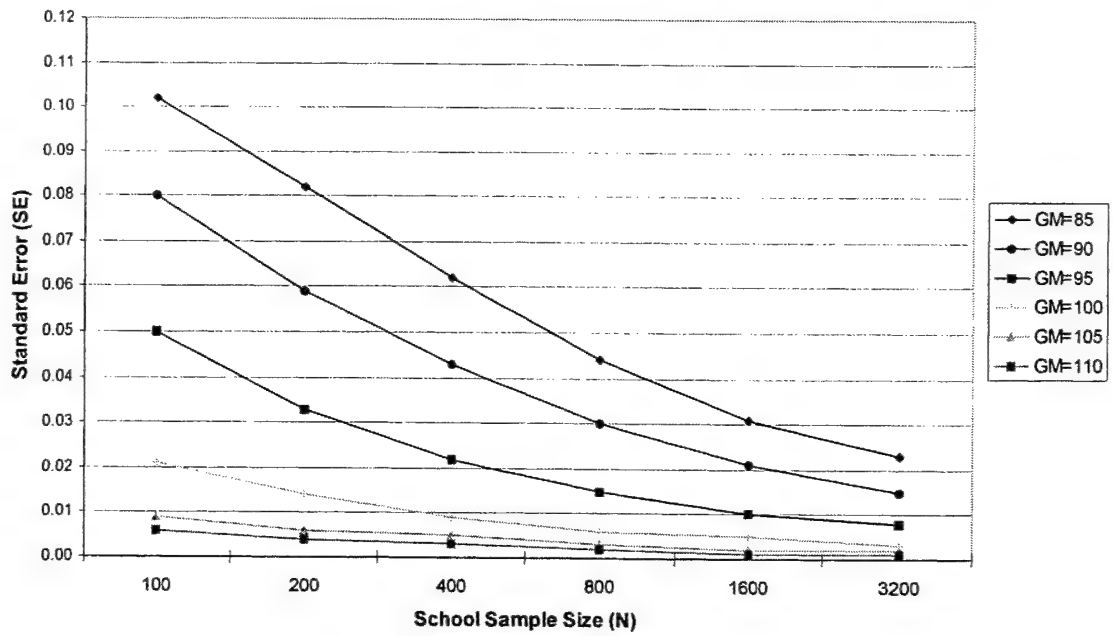
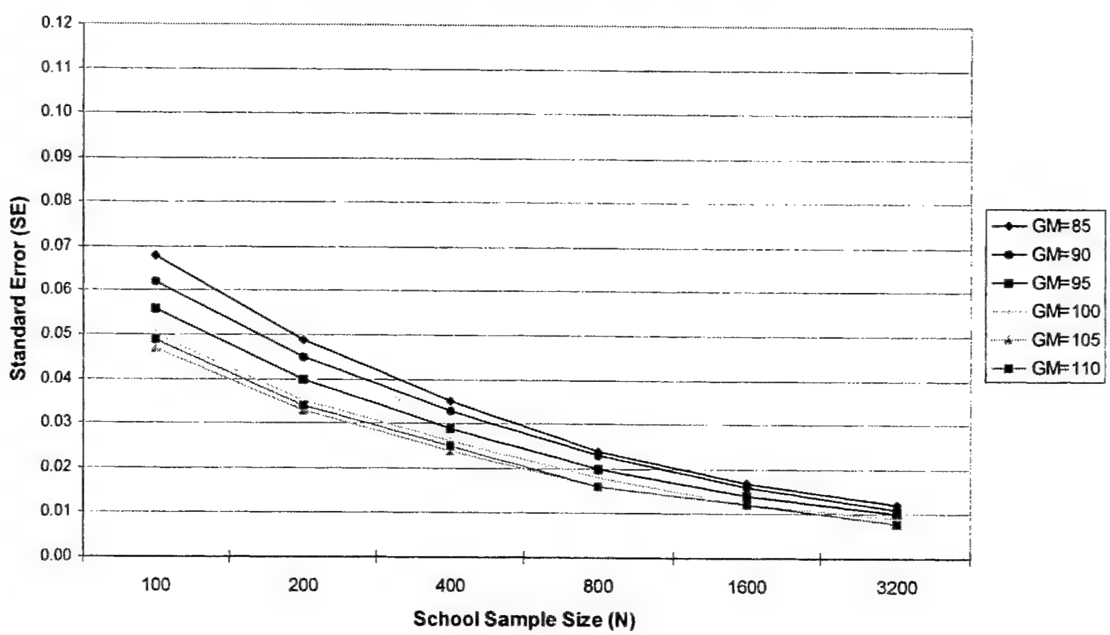


Figure 13. Results for Medium Difficulty, Low Complexity Condition
Standard Errors (SEs) by Cut Score and N



Standard Errors (SEs) by Cut Score and Sample Size (N)

Figure 14. Results for Medium Difficulty, Medium Complexity Condition
Standard Errors (SEs) by Cut Score and N

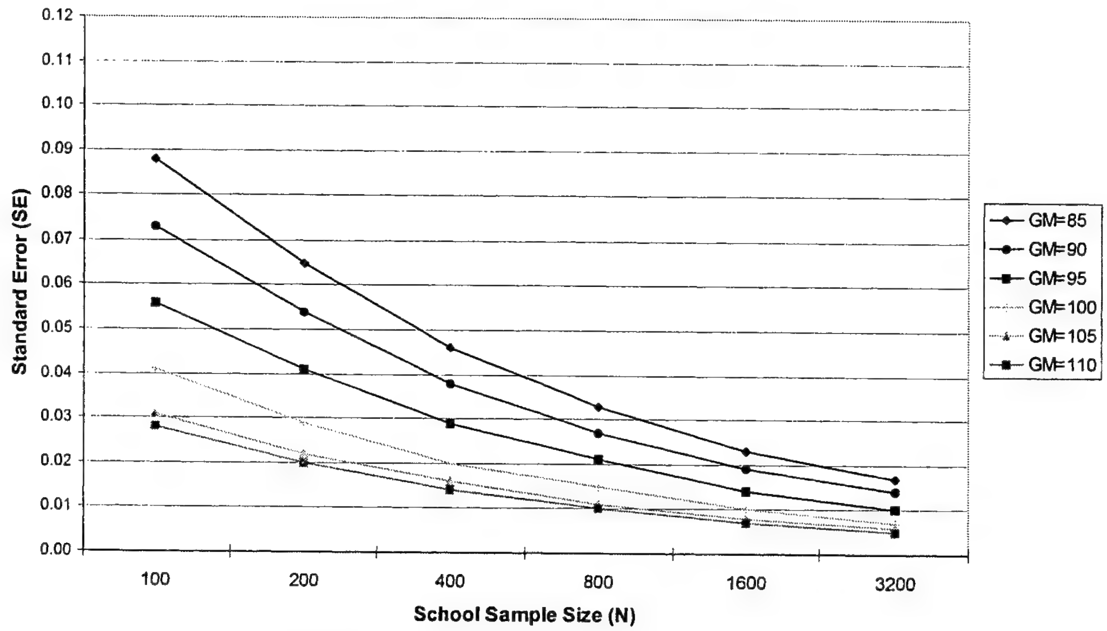
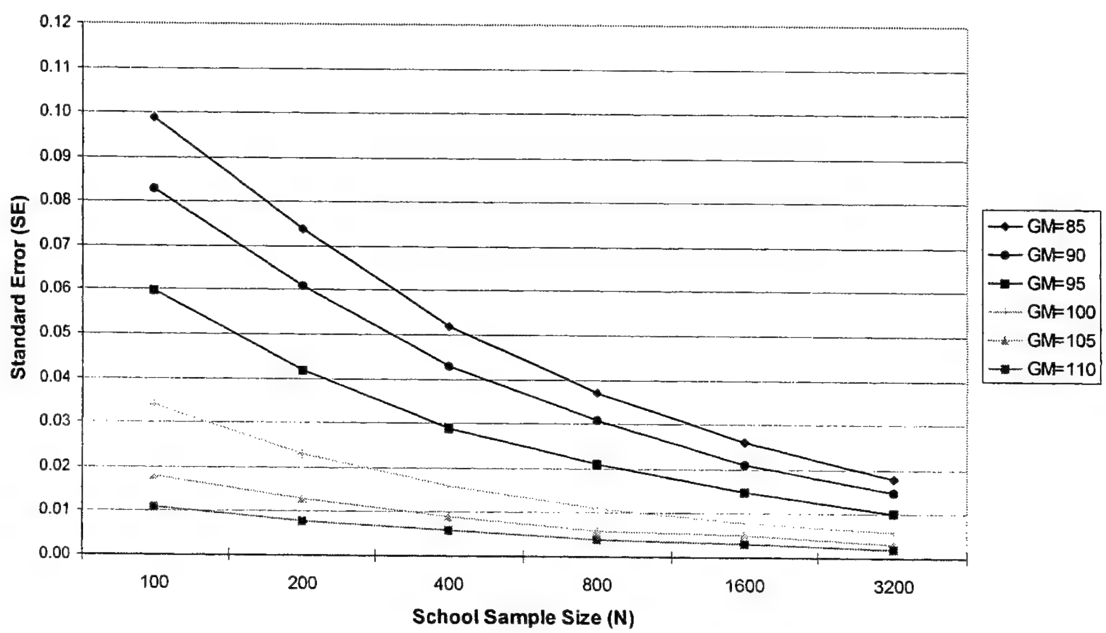


Figure 15. Results for Medium Difficulty, High Complexity Condition
Standard Errors (SEs) by Cut Score and N



Standard Errors (SEs) by Cut Score and Sample Size (N)

Figure 16. Results for High Difficulty, Low Complexity Condition Standard Errors (SEs) by Cut Score and N

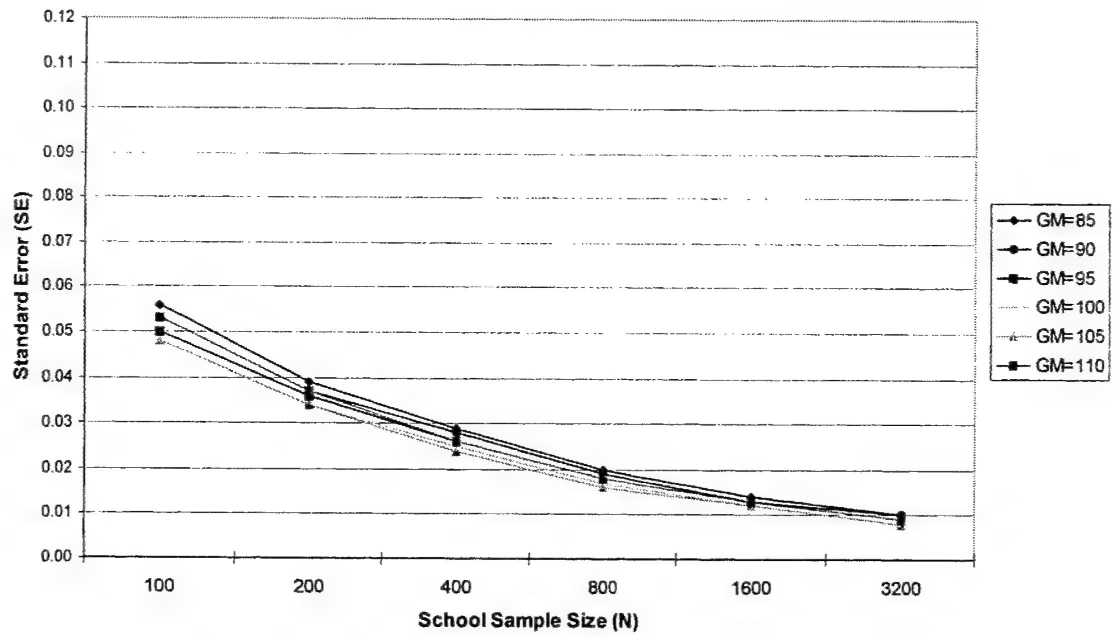
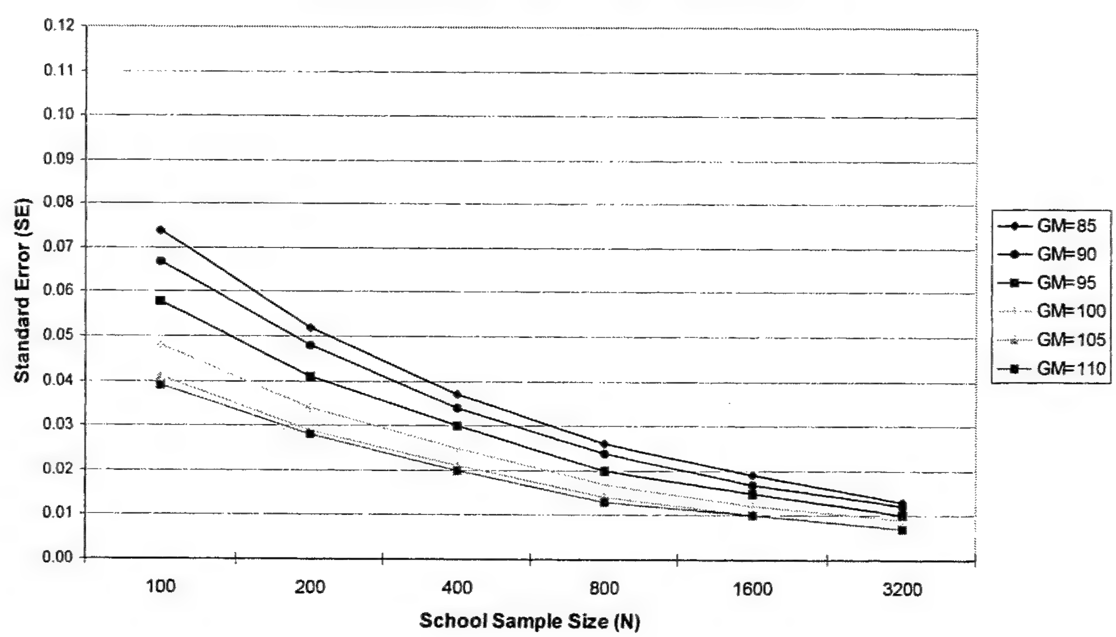
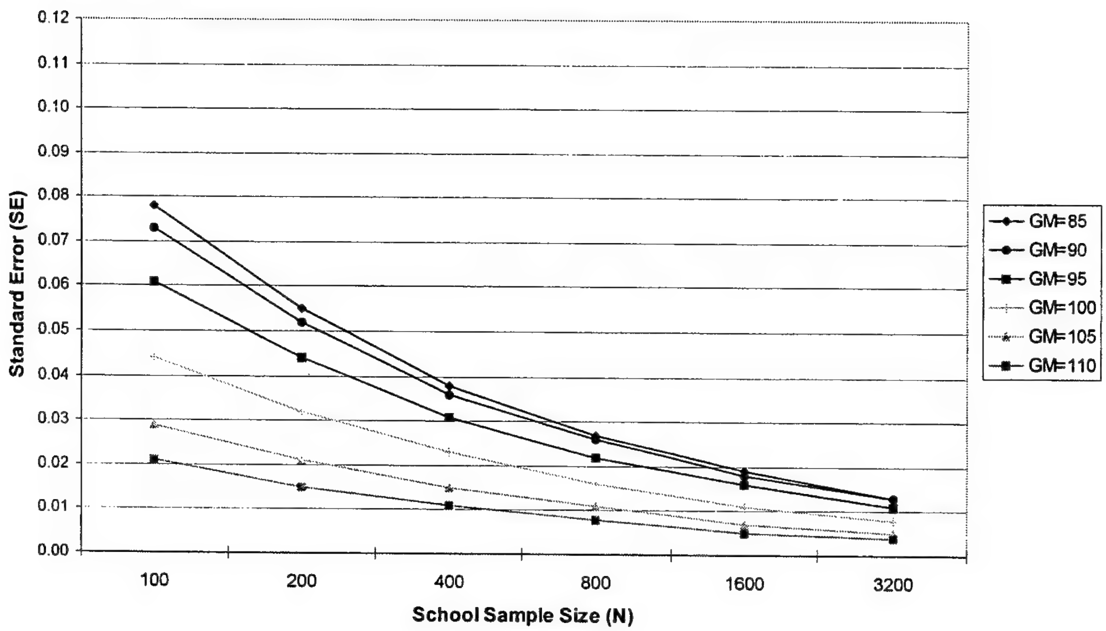


Figure 17. Results for High Difficulty, Medium Complexity Condition Standard Errors (SEs) by Cut Score and N



Standard Errors (SEs) by Cut Score and Sample Size (N)

Figure 18. Results for High Difficulty, High Complexity Condition
Standard Errors (SEs) by Cut Score and N



Percent Reduction in Standard Error (SE) by Cut Score and Sample Size (N)

Figure 19. Results for Low Difficulty, Low Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N

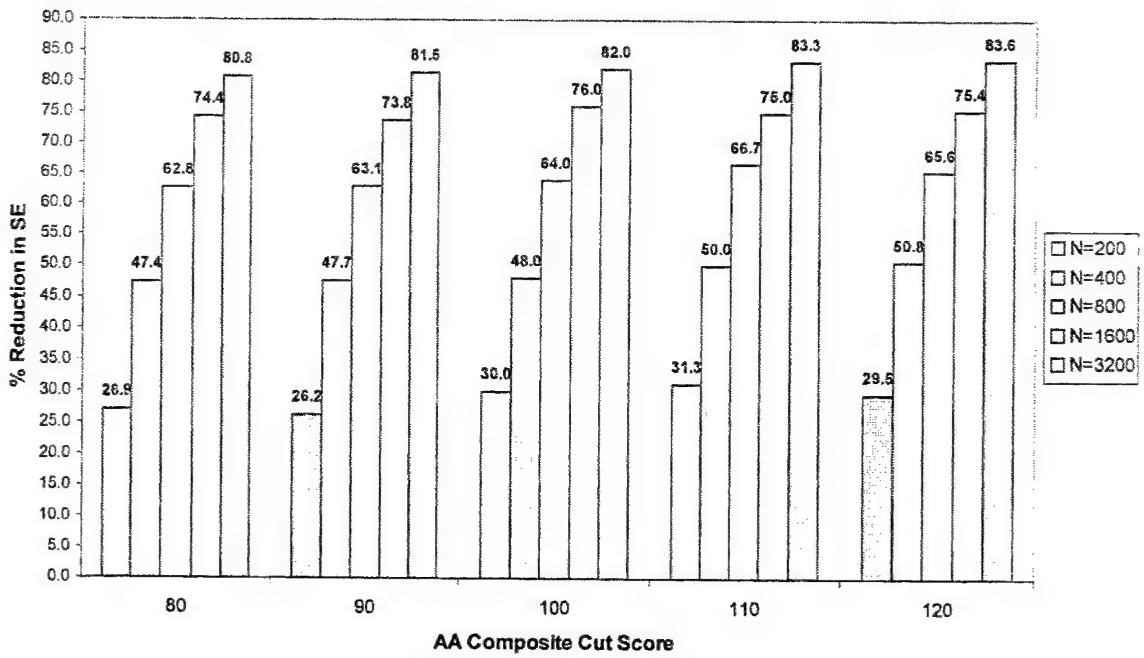
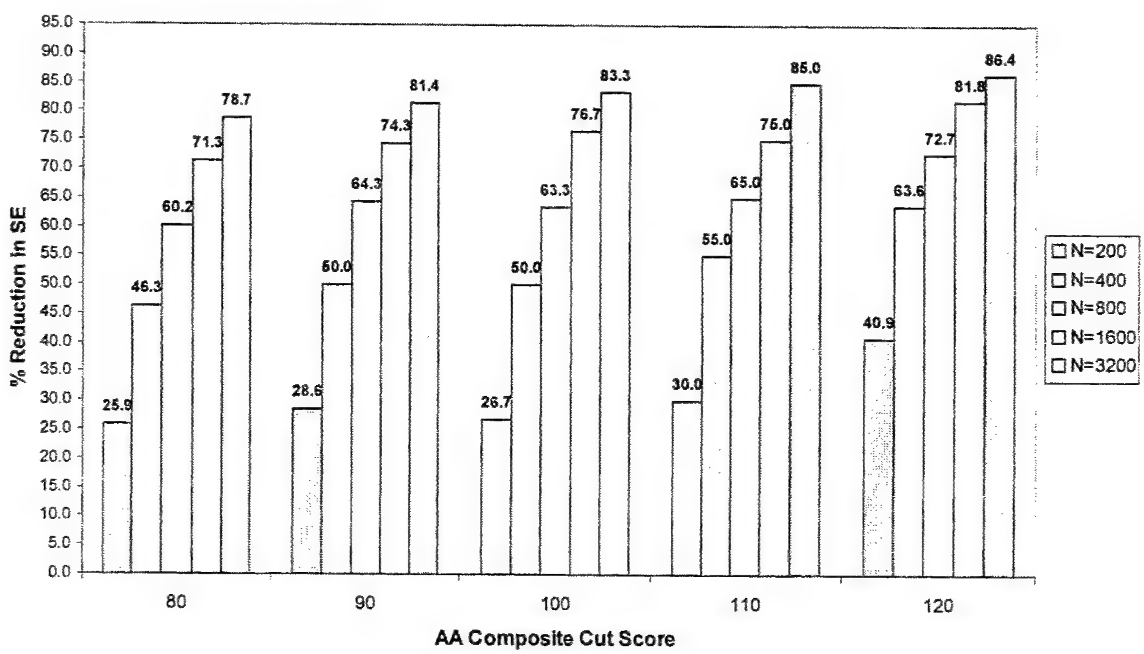


Figure 20. Results for Low Difficulty, Medium Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N



Percent Reduction in Standard Error (SE) by Cut Score and Sample Size (N)

Figure 21. Results for Low Difficulty, High Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N

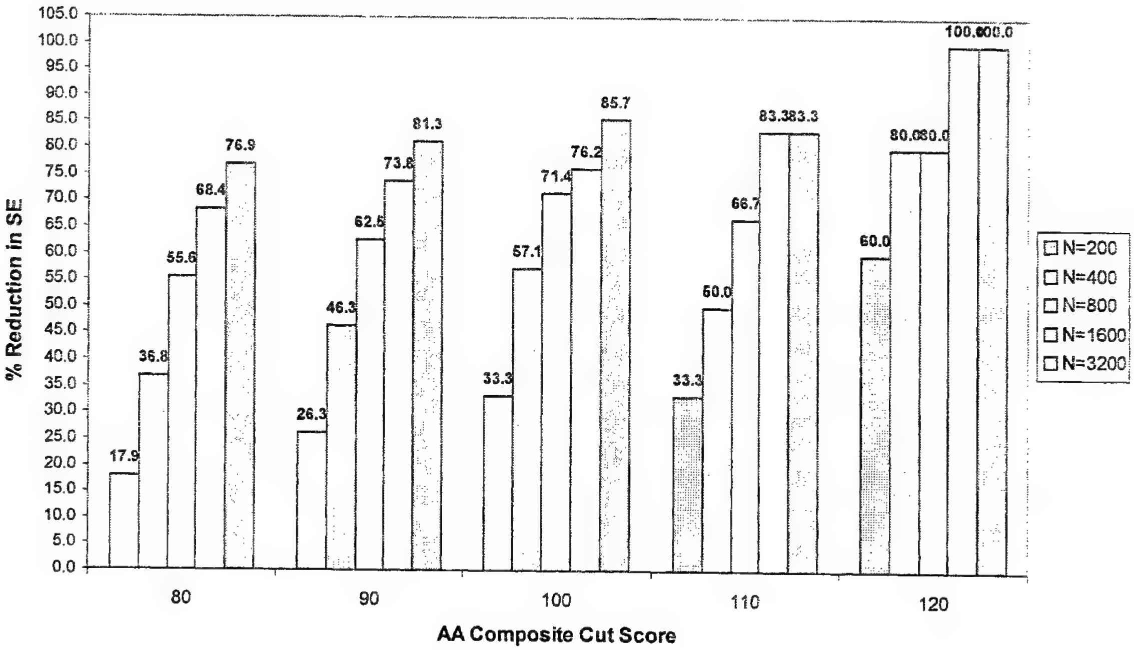
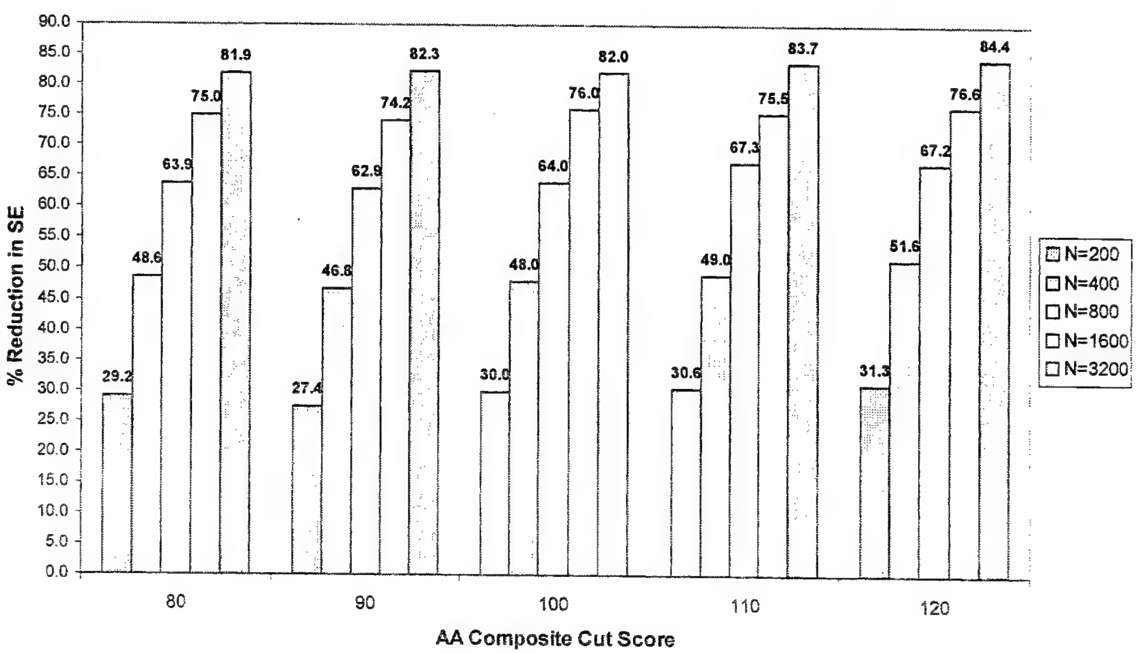


Figure 22. Results for Medium Difficulty, Low Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N



Percent Reduction in Standard Error (SE) by Cut Score and Sample Size (N)

Figure 23. Results for Medium Difficulty, Medium Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N

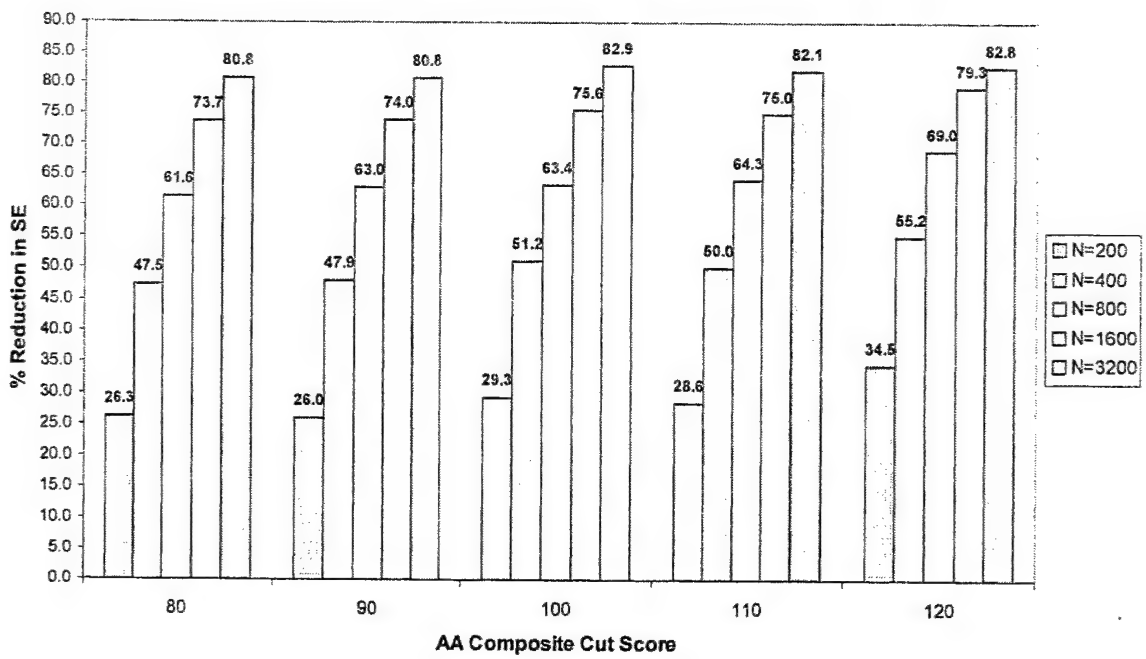
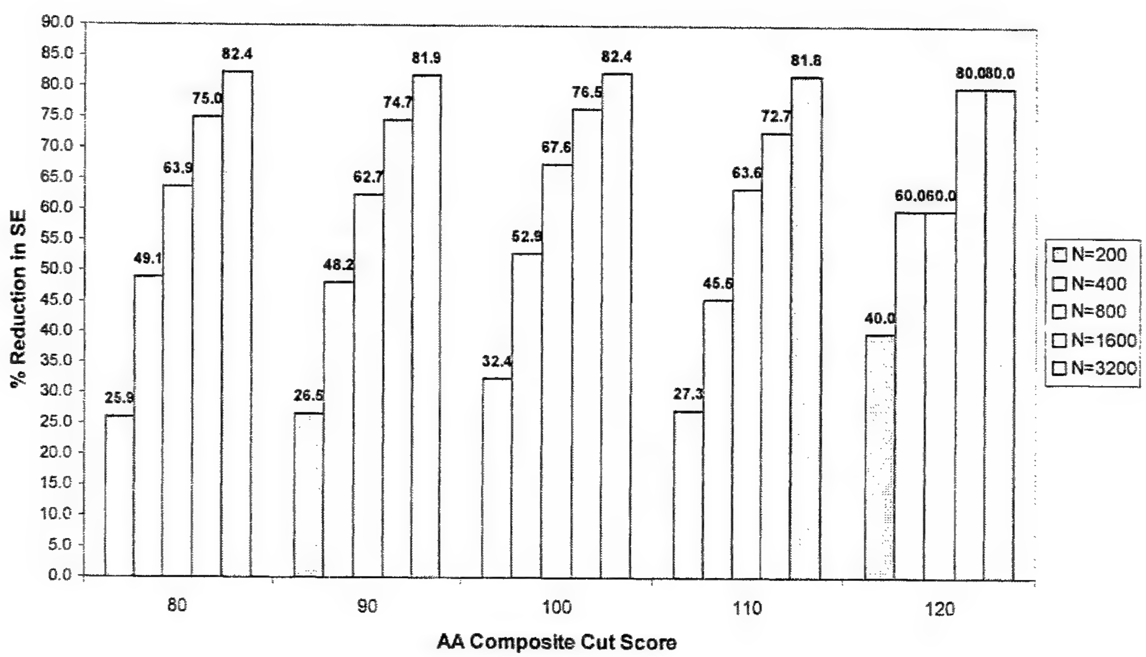


Figure 24. Results for Medium Difficulty, High Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N



Percent Reduction in Standard Error (SE) by Cut Score and Sample Size (N)

Figure 25. Results for High Difficulty, Low Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N

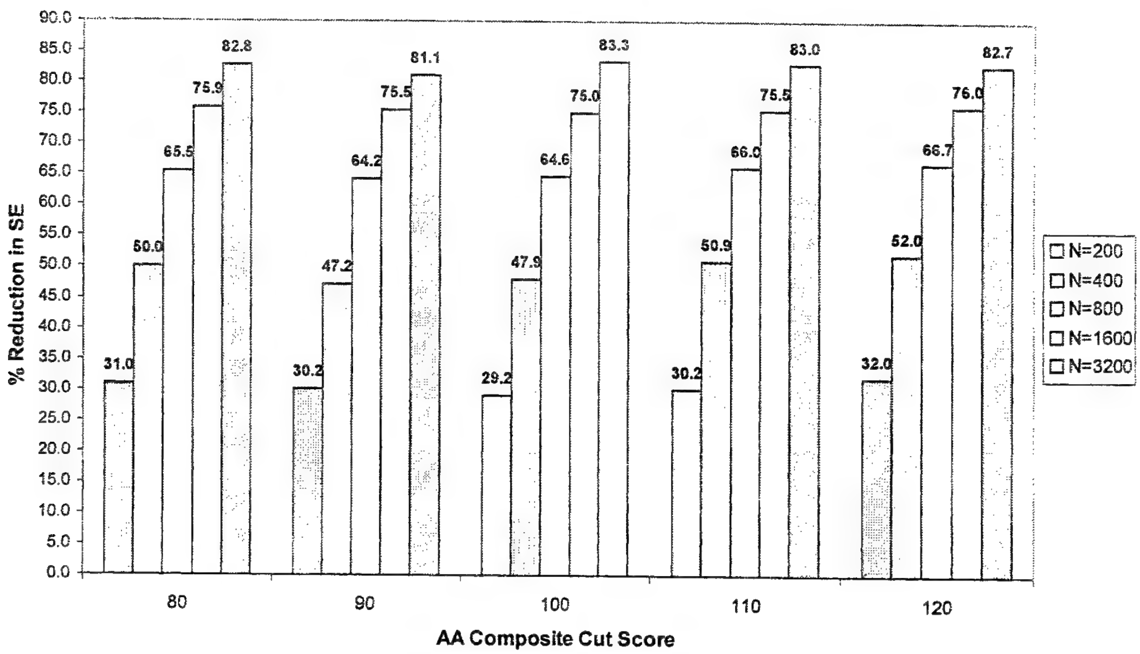
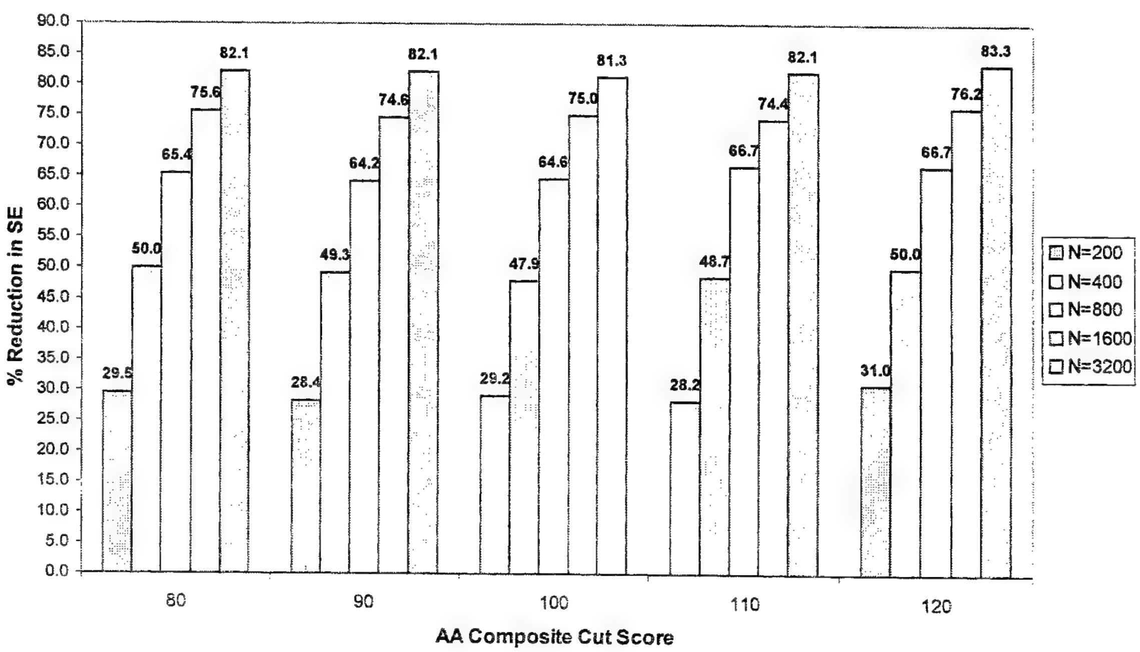
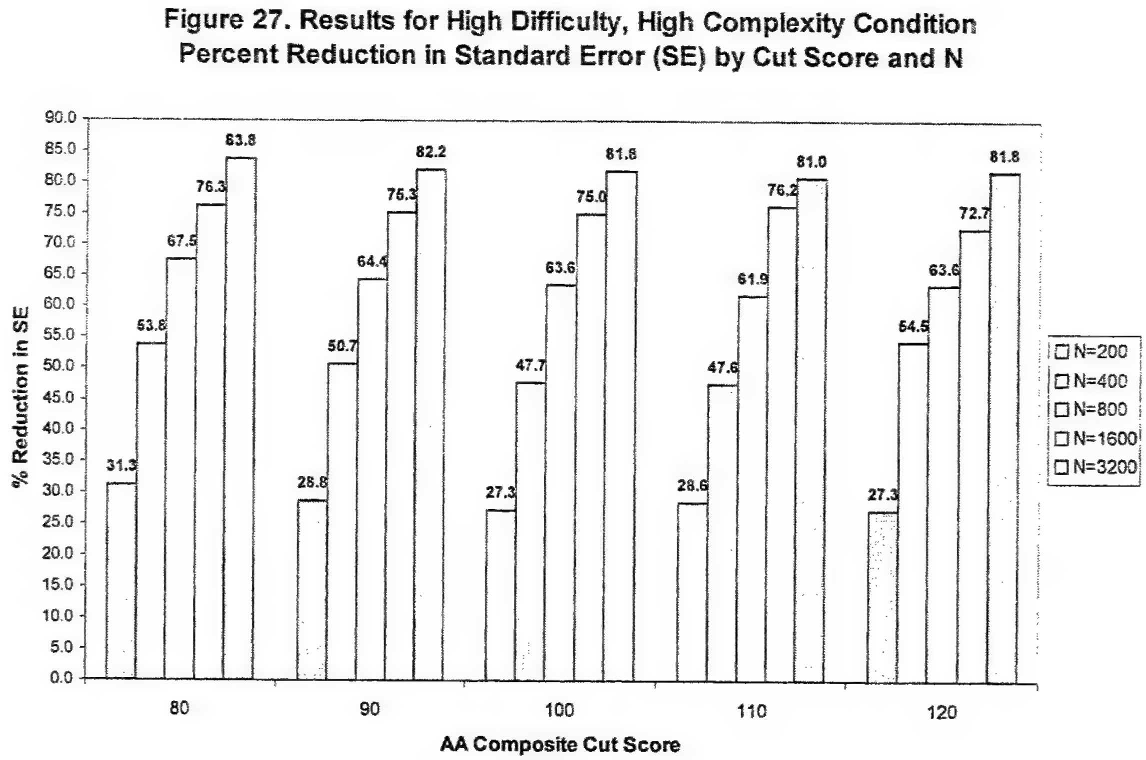


Figure 26. Results for High Difficulty, Medium Complexity Condition
Percent Reduction in Standard Error (SE) by Cut Score and N



Percent Reduction in Standard Error (SE) by Cut Score and Sample Size (N)



Coefficient of Variation by Cut Score and Sample Size (N)

Figure 28. Results for Low Difficulty, Low Complexity Condition
Coefficient of Variation by Cut Score and N

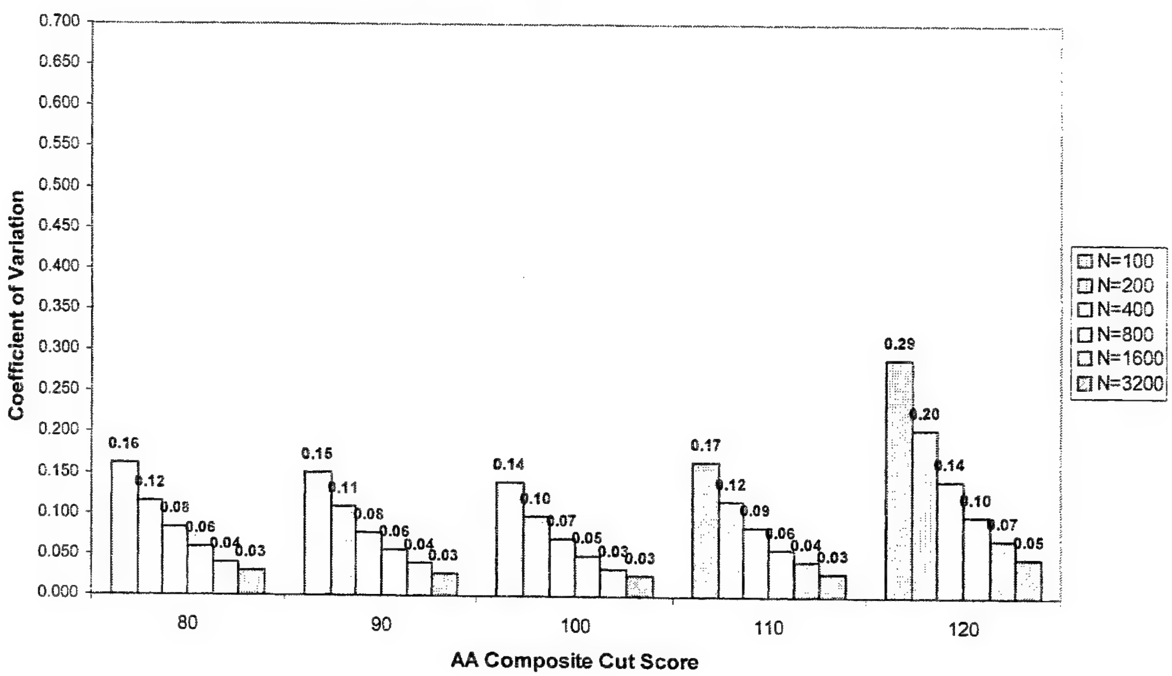
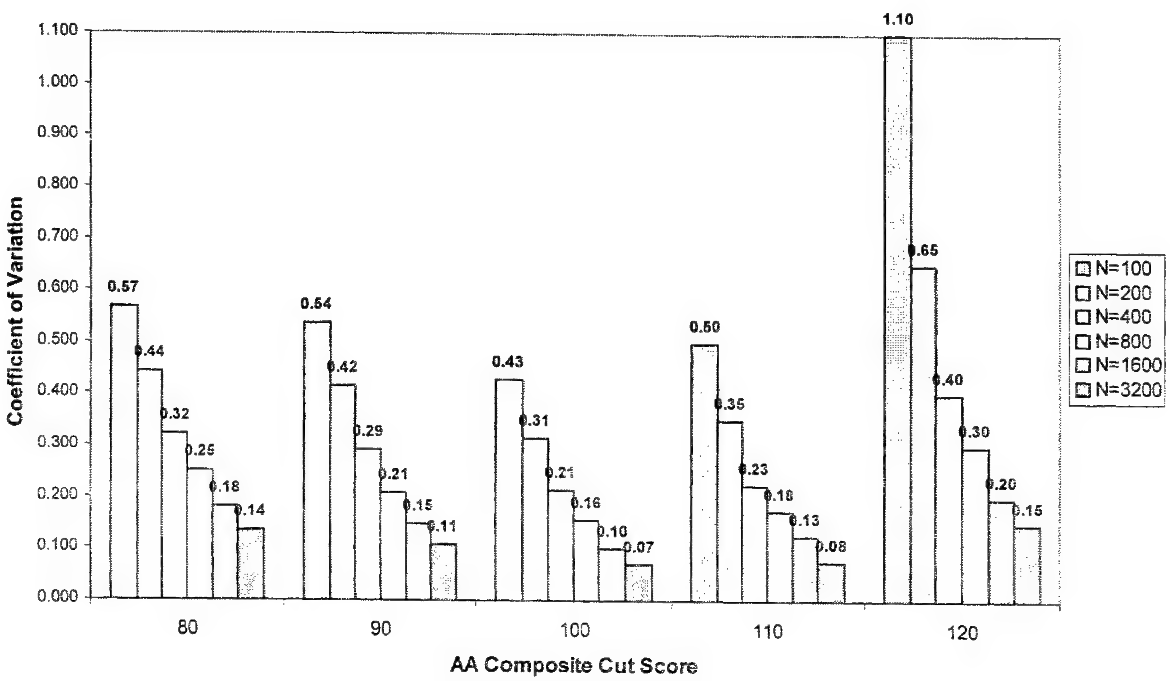


Figure 29. Results for Low Difficulty, Medium Complexity Condition
Coefficient of Variation by Cut Score and N



Coefficient of Variation by Cut Score and Sample Size (N)

Figure 30. Results for Low Difficulty, High Complexity Condition
Coefficient of Variation by Cut Score and N

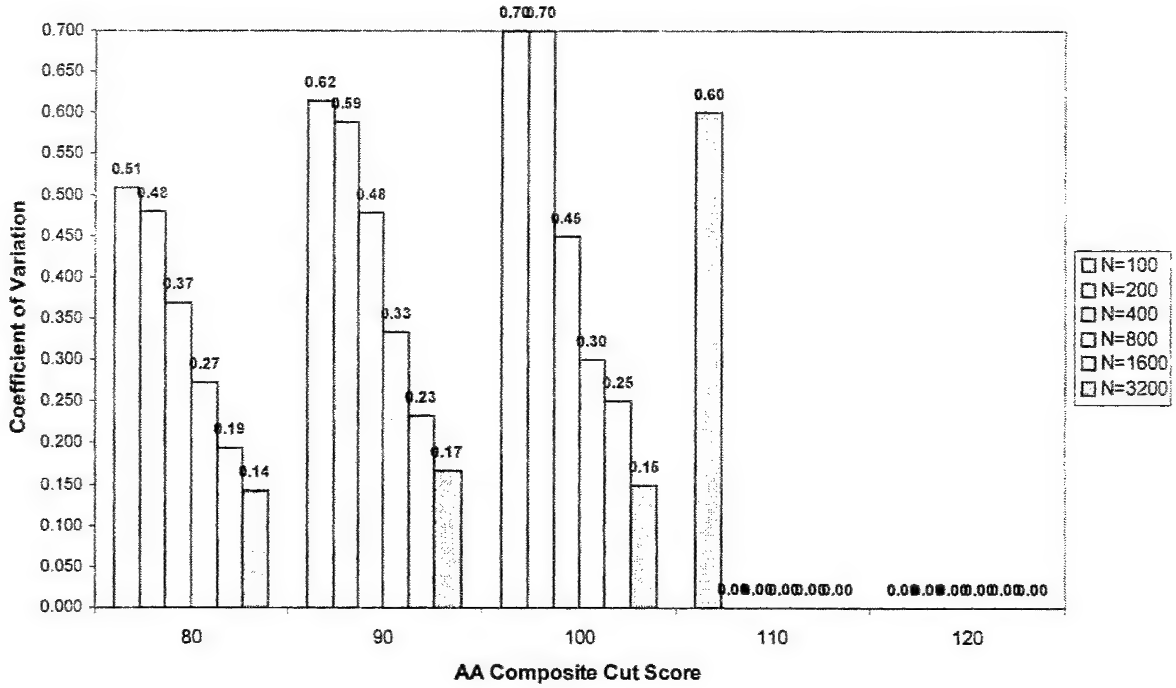
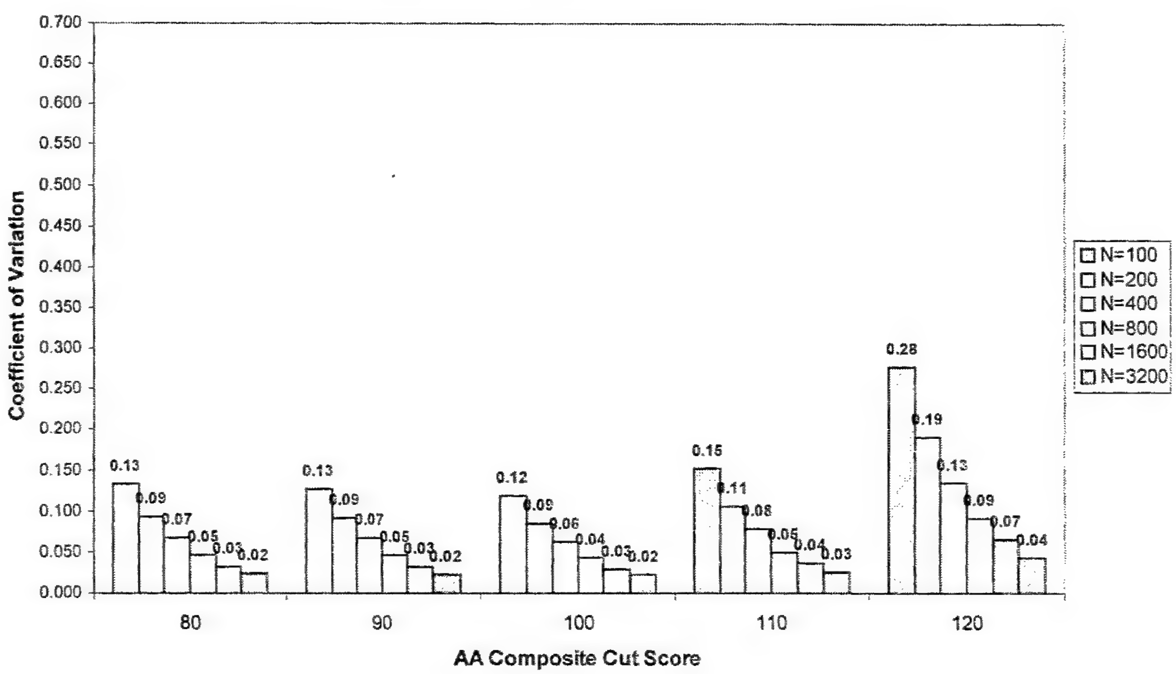


Figure 31. Results for Medium Difficulty, Low Complexity Condition
Coefficient of Variation by Cut Score and N



Coefficient of Variation by Cut Score and Sample Size (N)

Figure 32. Results for Medium Difficulty, Medium Complexity Condition
Coefficient of Variation by Cut Score and N

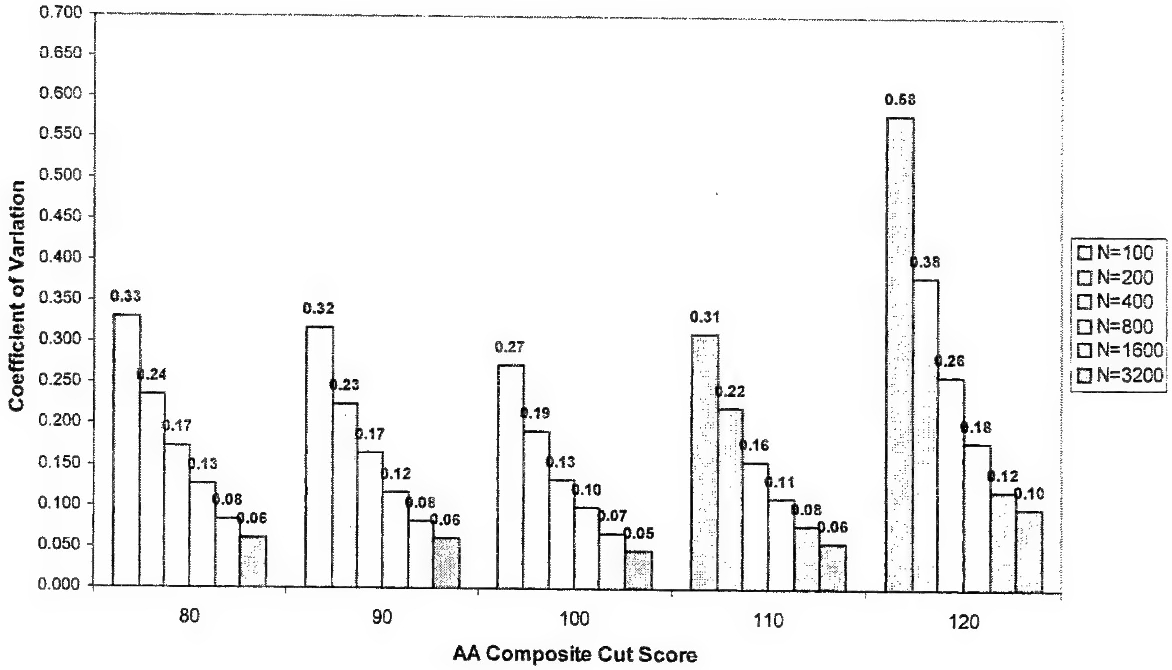
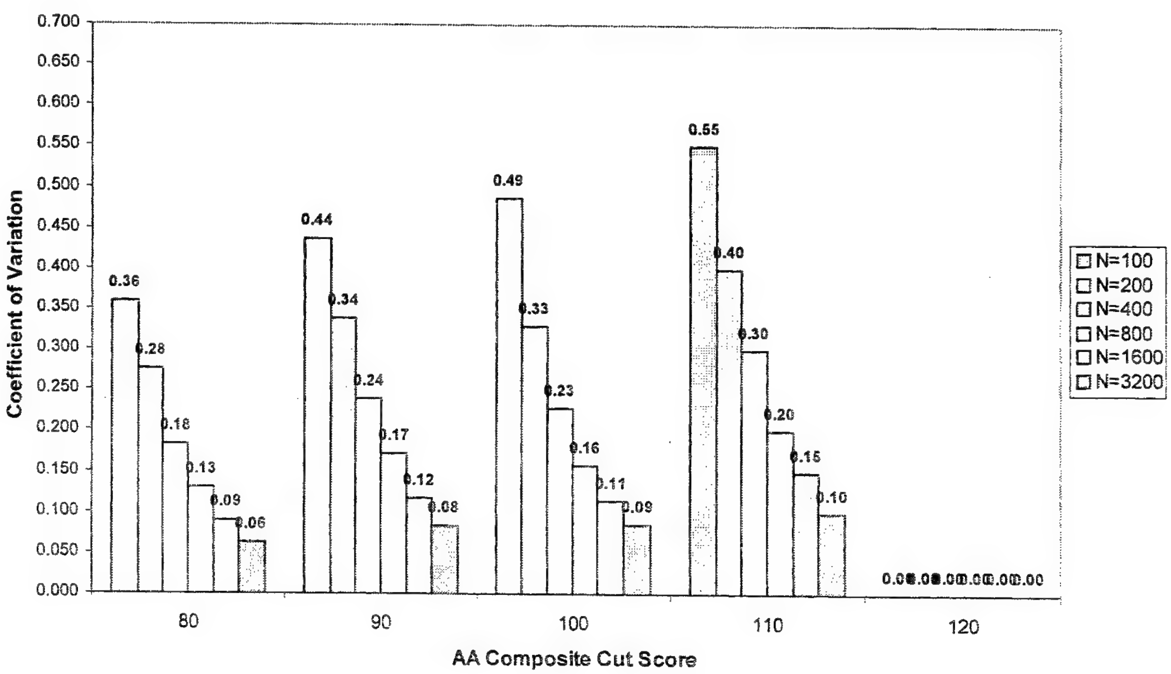


Figure 33. Results for Medium Difficulty, High Complexity Condition
Coefficient of Variation by Cut Score and N



Coefficient of Variation by Cut Score and Sample Size (N)

Figure 34. Results for High Difficulty, Low Complexity Condition
Coefficient of Variation by Cut Score and N

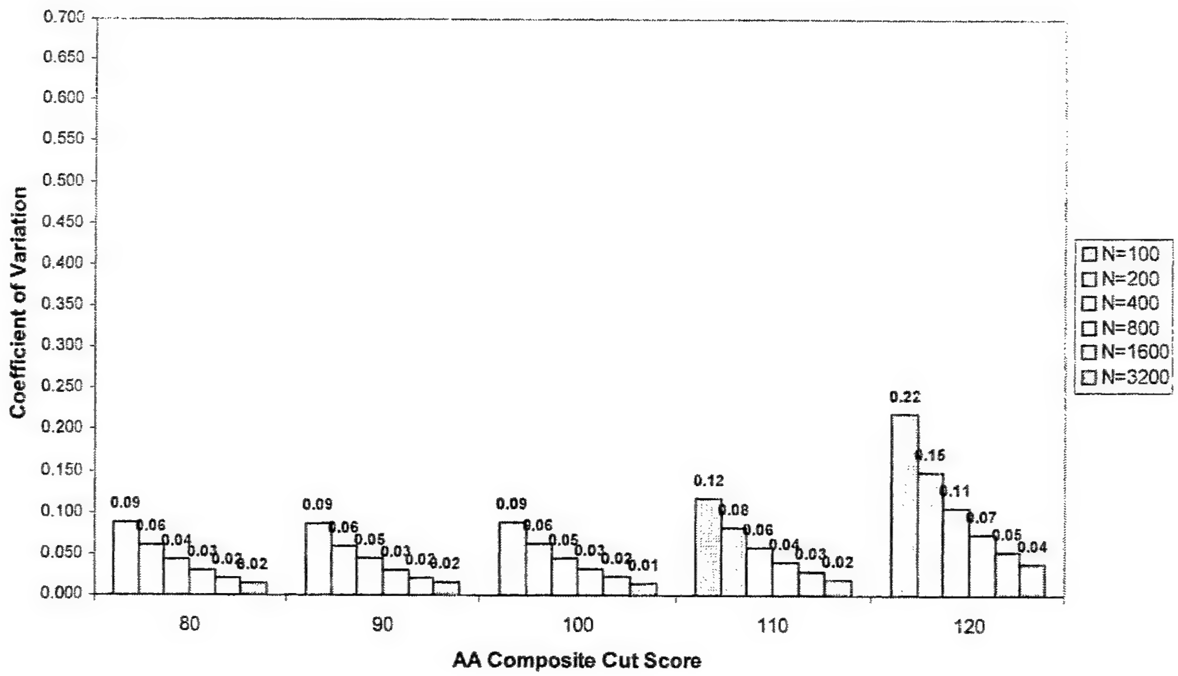
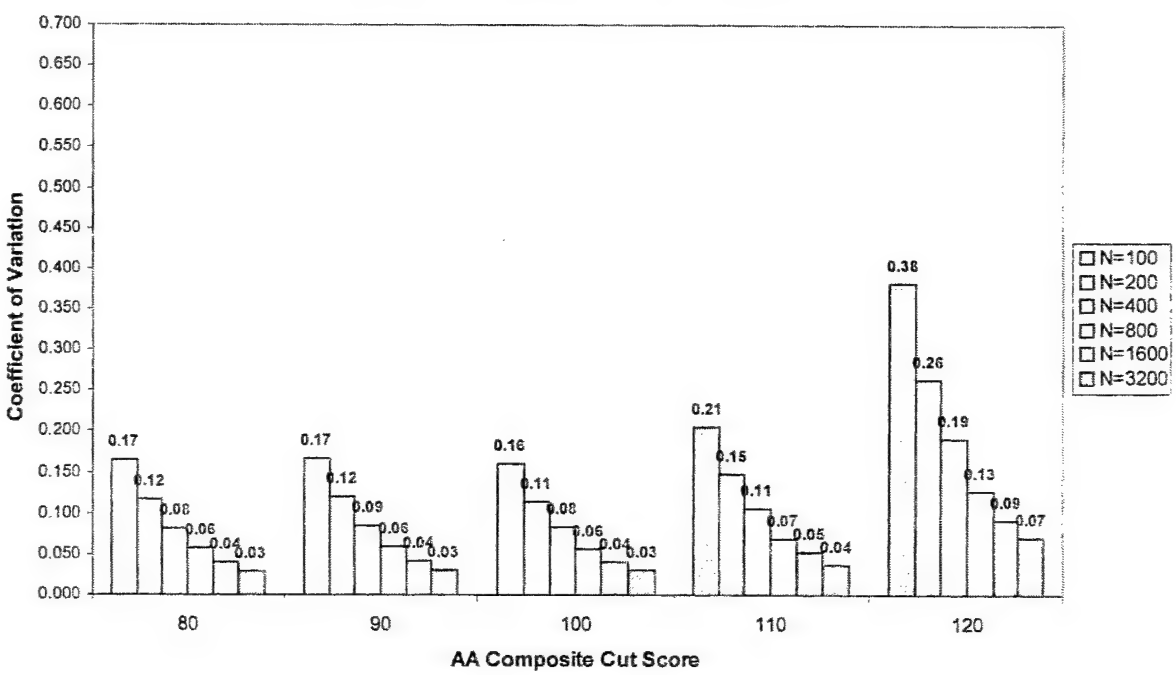
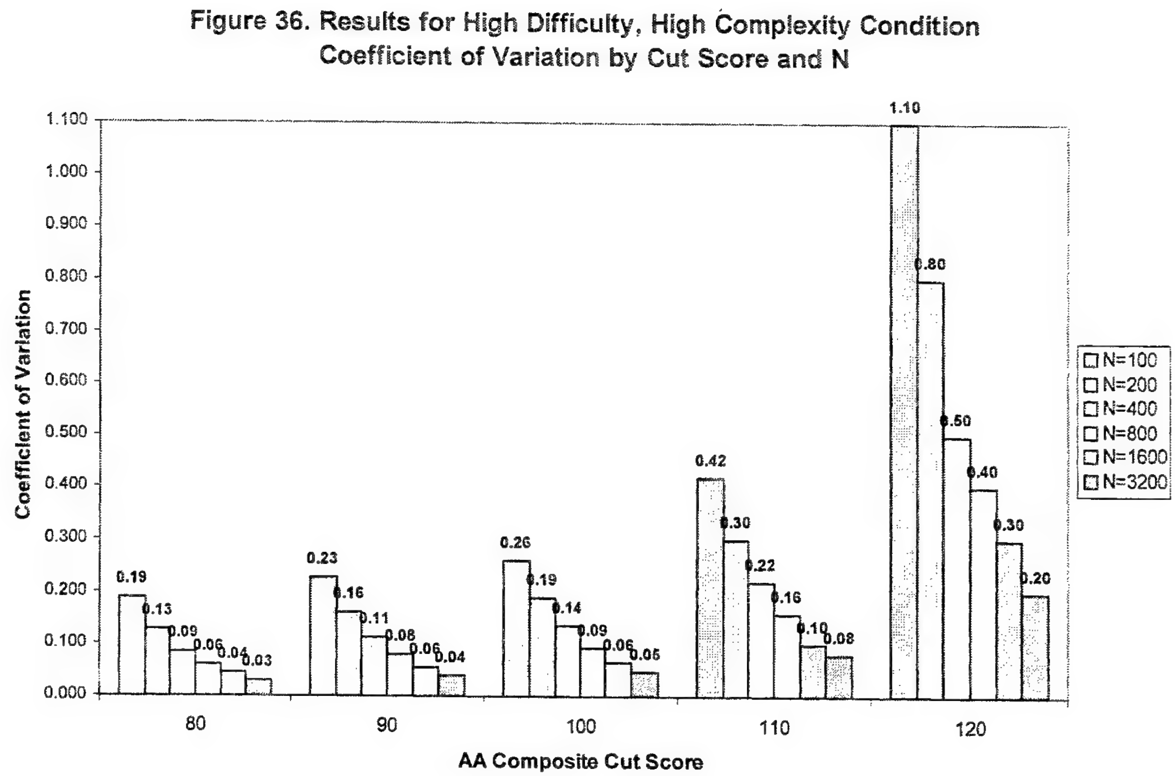


Figure 35. Results for High Difficulty, Medium Complexity Condition
Coefficient of Variation by Cut Score and N



Coefficient of Variation by Cut Score and Sample Size (N)



Results for Training Difficulty (Low, Medium, High)
Average Attrition Rates by Cut Score and Sample Size (N)

Figure 37. Results for Training Difficulty (Low, Medium, High)
Attrition Rates by Cut Score for N=100

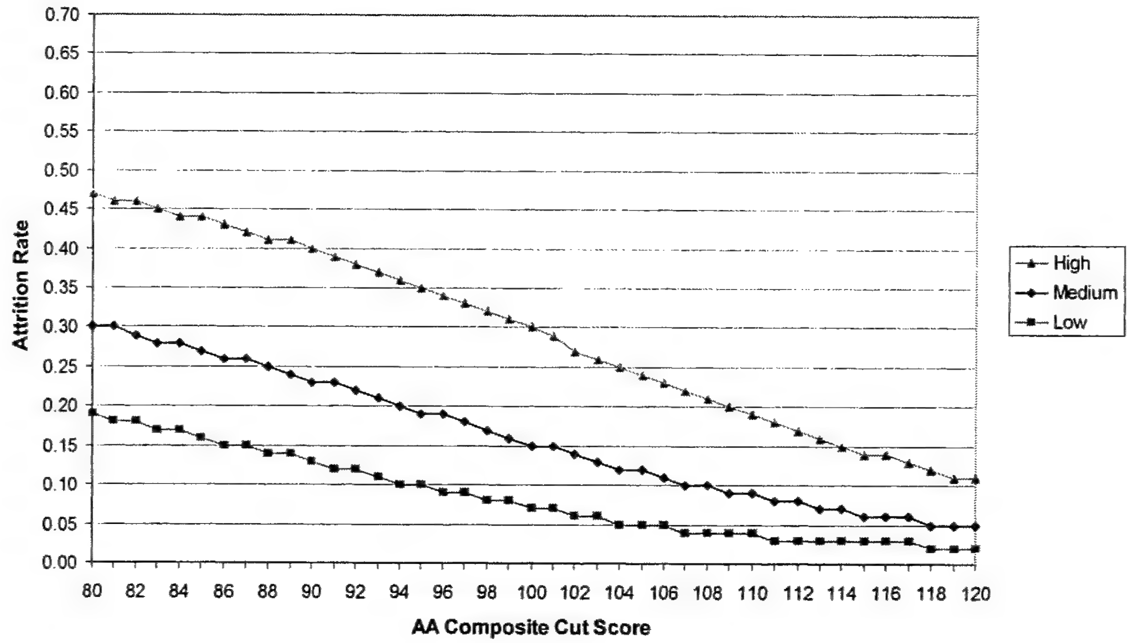
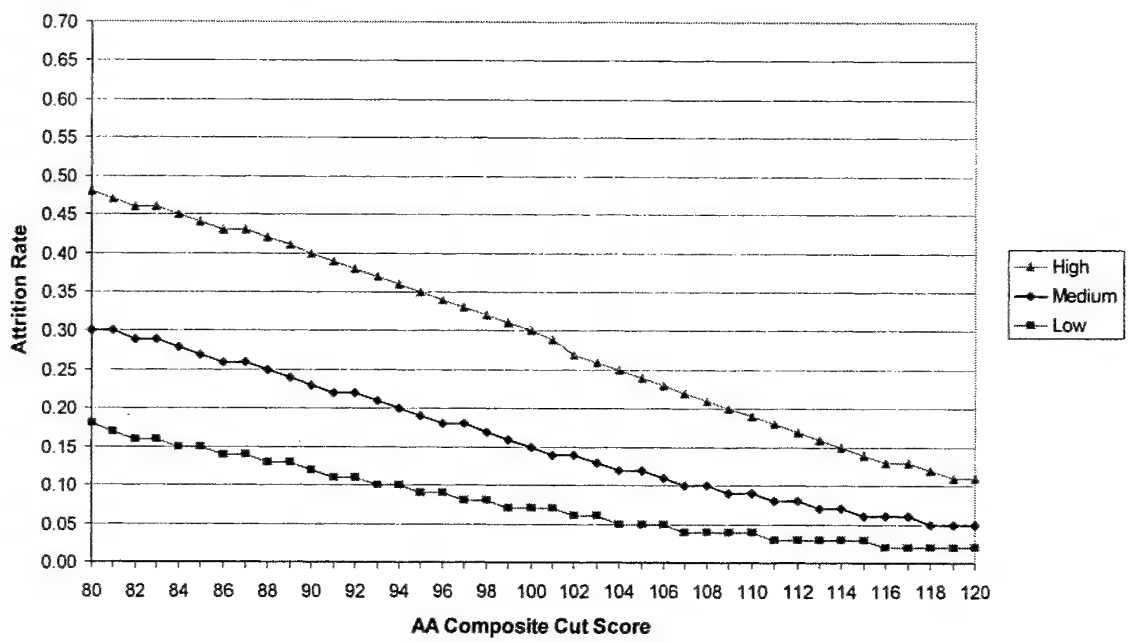


Figure 38. Results for Training Difficulty (Low, Medium, High)
Attrition Rates by Cut Score for N=400



Results for Training Difficulty (Low, Medium, High)
Average Attrition Rates by Cut Score and Sample Size (N)

Figure 39. Results for Training Difficulty (Low, Medium, High) Attrition Rates by Cut Score for N=800

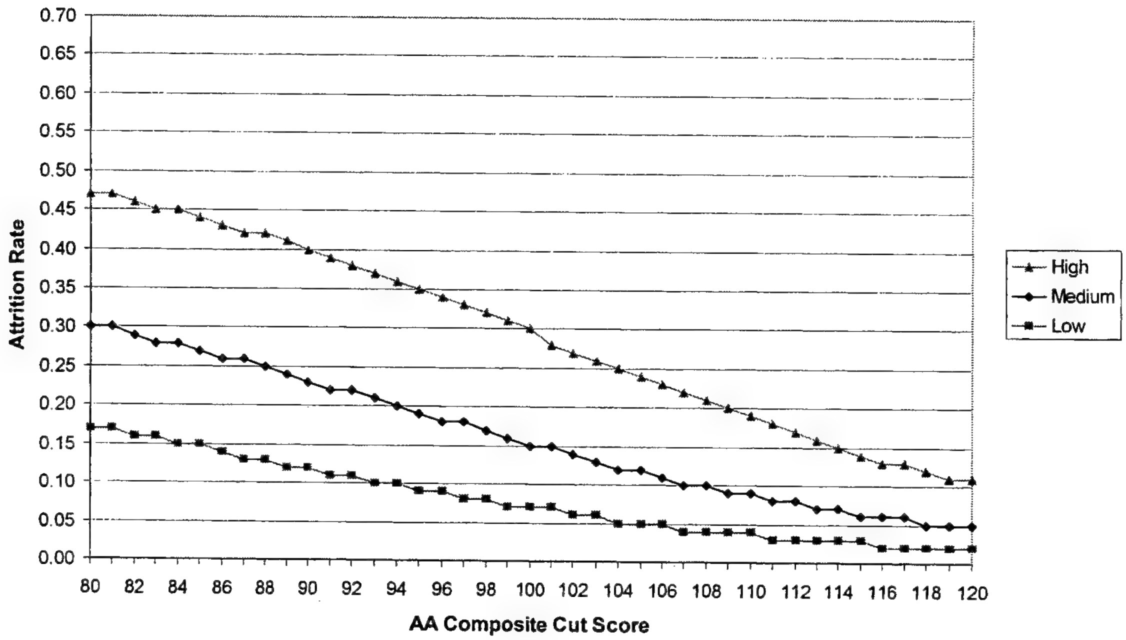
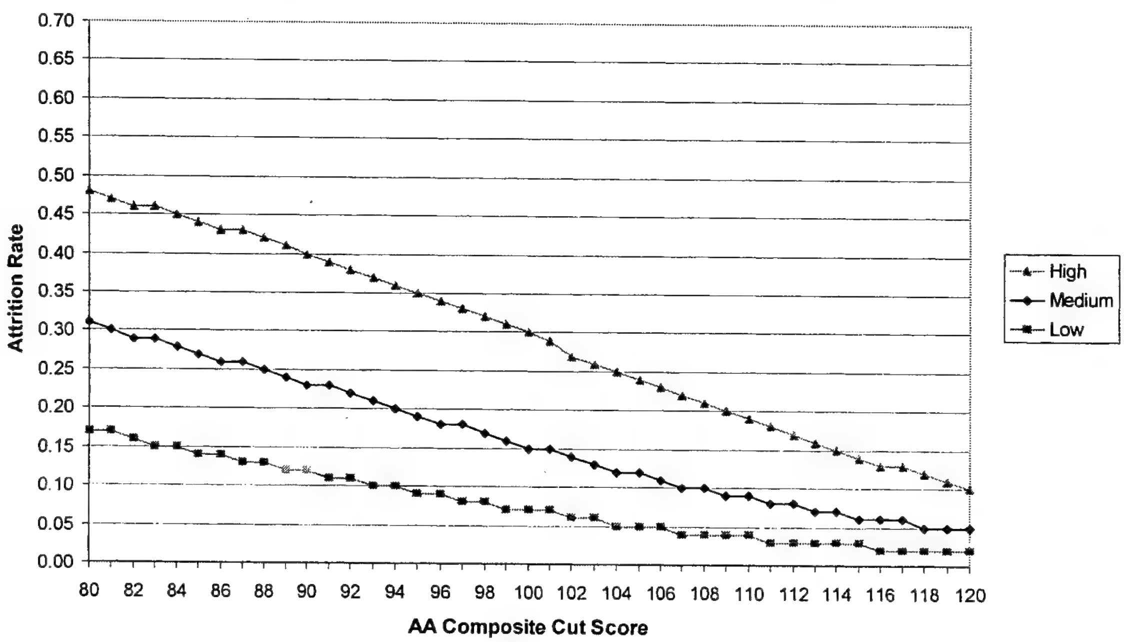


Figure 40. Results for Training Difficulty (Low, Medium, High) Attrition Rates by Cut Score for N=3200



Results for Training Difficulty (Low, Medium, High)
Standard Error (SE) by Sample Size (N) and Cut Score

Figure 41. Results for Training Difficulty (Low, Medium, High) Standard Errors (SEs) by N for GM=85

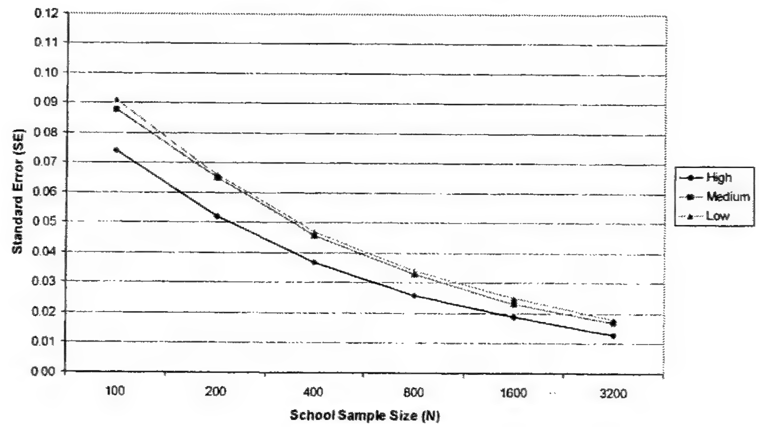


Figure 42. Results for Training Difficulty (Low, Medium, High) Standard Errors (SEs) by N for GM=95

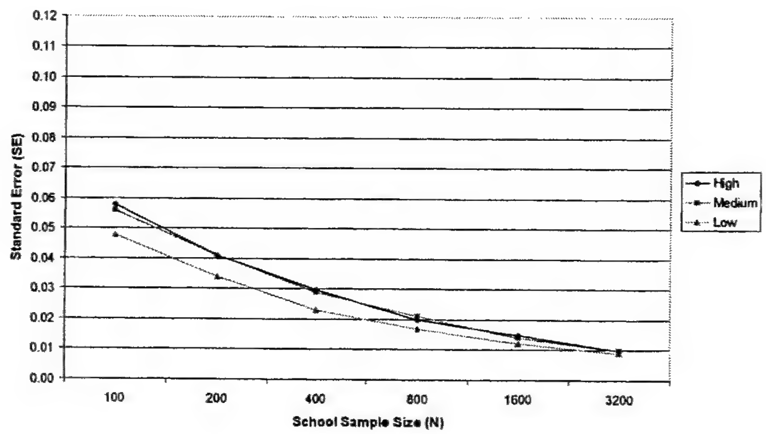
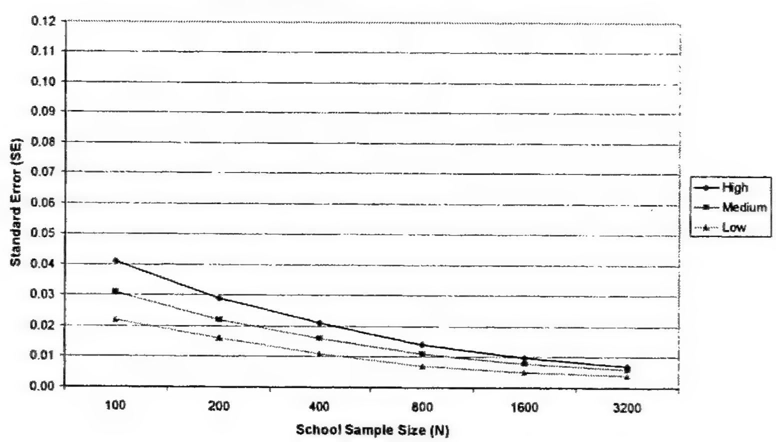


Figure 43. Results for Training Difficulty (Low, Medium, High) Standard Errors (SEs) by N for GM=105



Results for Job Complexity (Low, Medium, High)
Average Attrition Rates by Cut Score and Sample Size (N)

Figure 44. Results for Job Complexity (Low, Medium, High) Attrition Rates by Cut Score for N=100

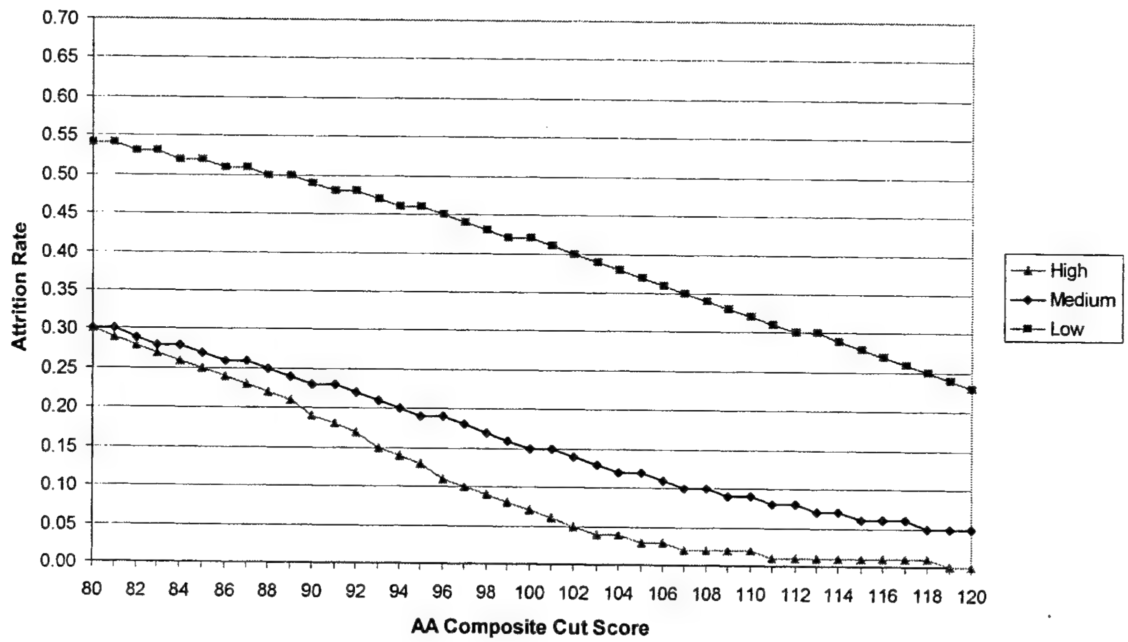
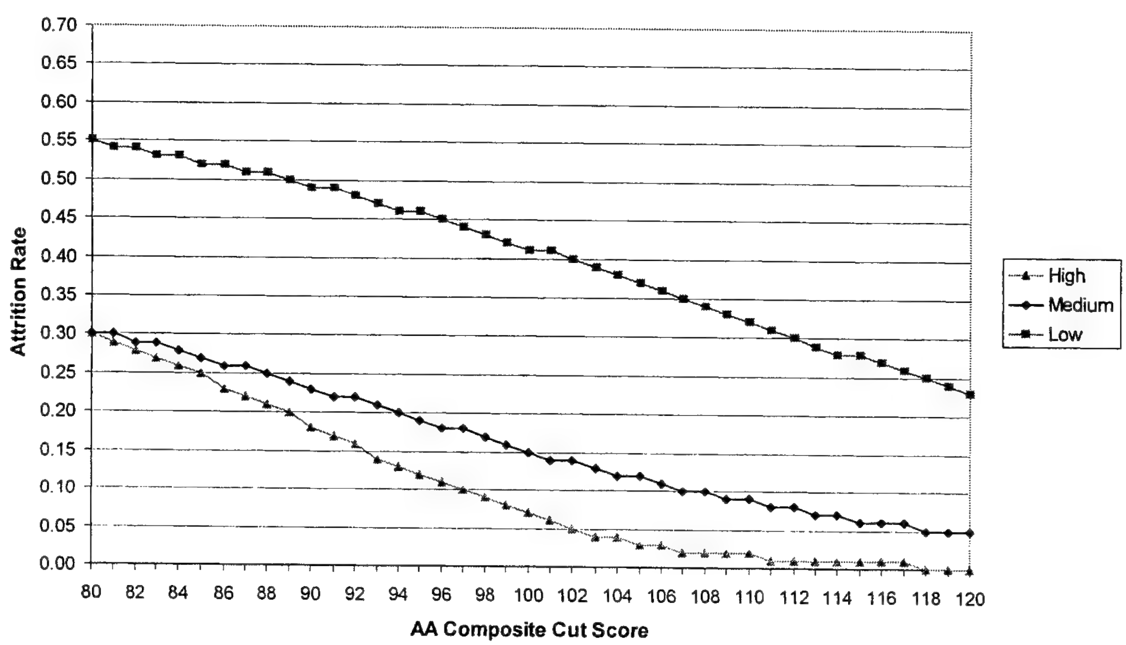


Figure 45. Results for Job Complexity (Low, Medium, High) Attrition Rates by Cut Score for N=400



Results for Job Complexity (Low, Medium, High)
Average Attrition Rates by Cut Score and Sample Size (N)

Figure 46. Results for Job Complexity (Low, Medium, High) Attrition Rates by Cut Score for N=800

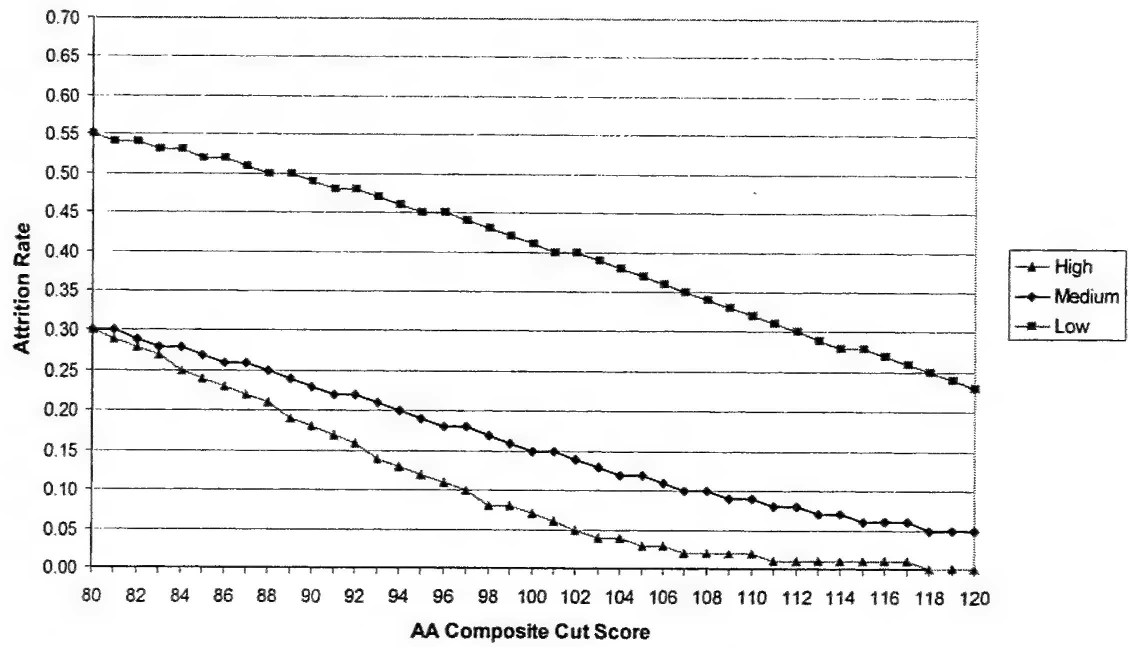
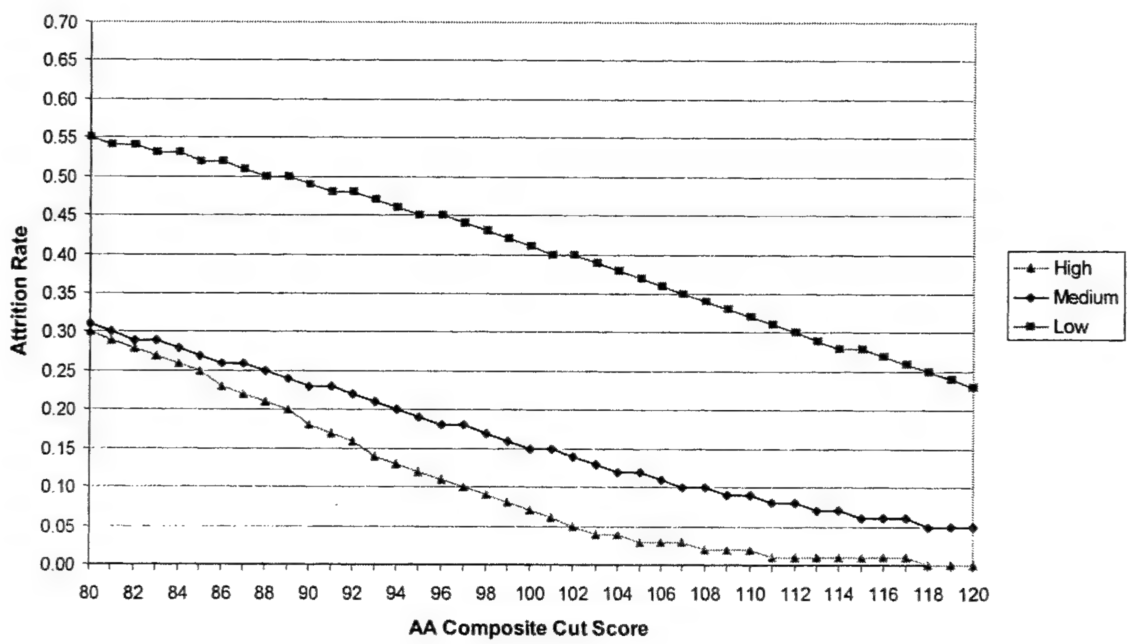


Figure 47. Results for Job Complexity (Low, Medium, High) Attrition Rates by Cut Score for N=3200



Results for Job Complexity (Low, Medium, High) Standard Error (SE) by Sample Size (N) and Cut Score

Figure 48. Results for Job Complexity (Low, Medium, High) Standard Errors (SEs) by N for GM=85

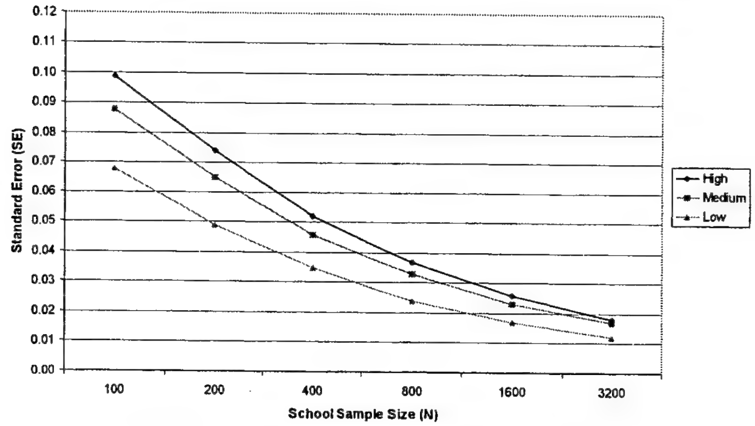


Figure 49. Results for Job Complexity (Low, Medium, High) Standard Errors (SEs) by N for GM=95

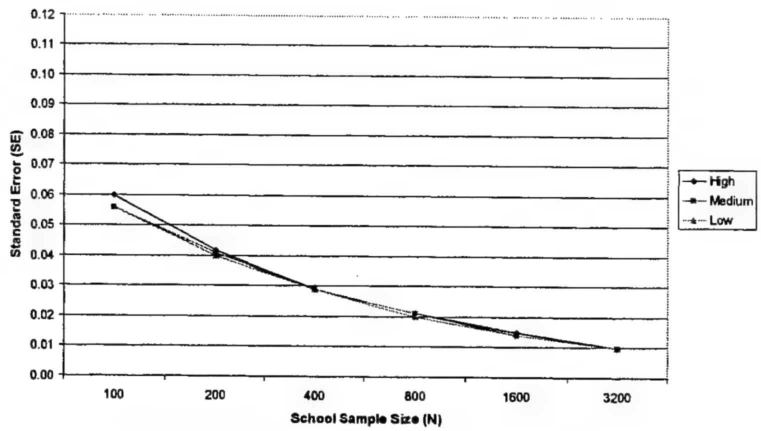
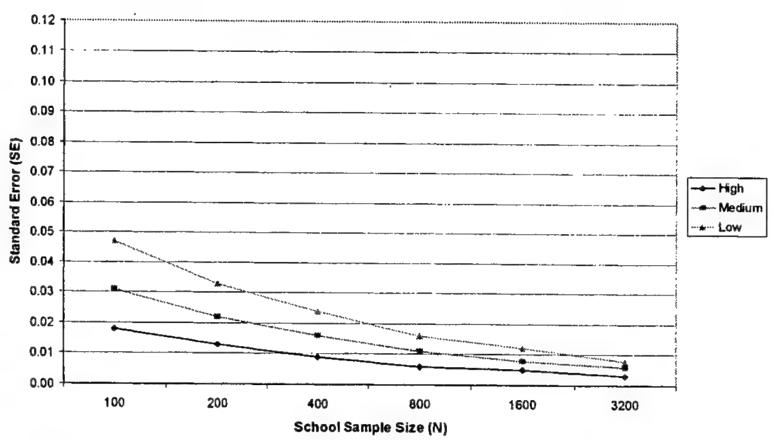


Figure 50. Results for Job Complexity (Low, Medium, High) Standard Errors (SEs) by N for GM=105



Attrition Rates with Standard Errors (SE)
by Cut Score and N

Figure 51. Attrition Rates with Standard Errors (SEs) by Cut Score for N=200

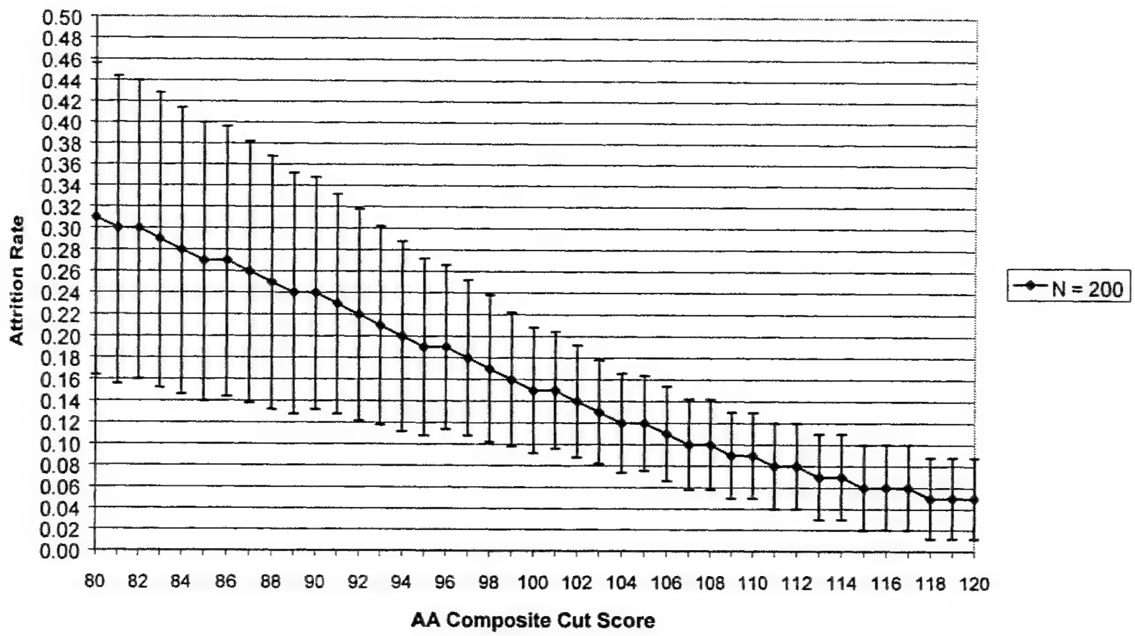
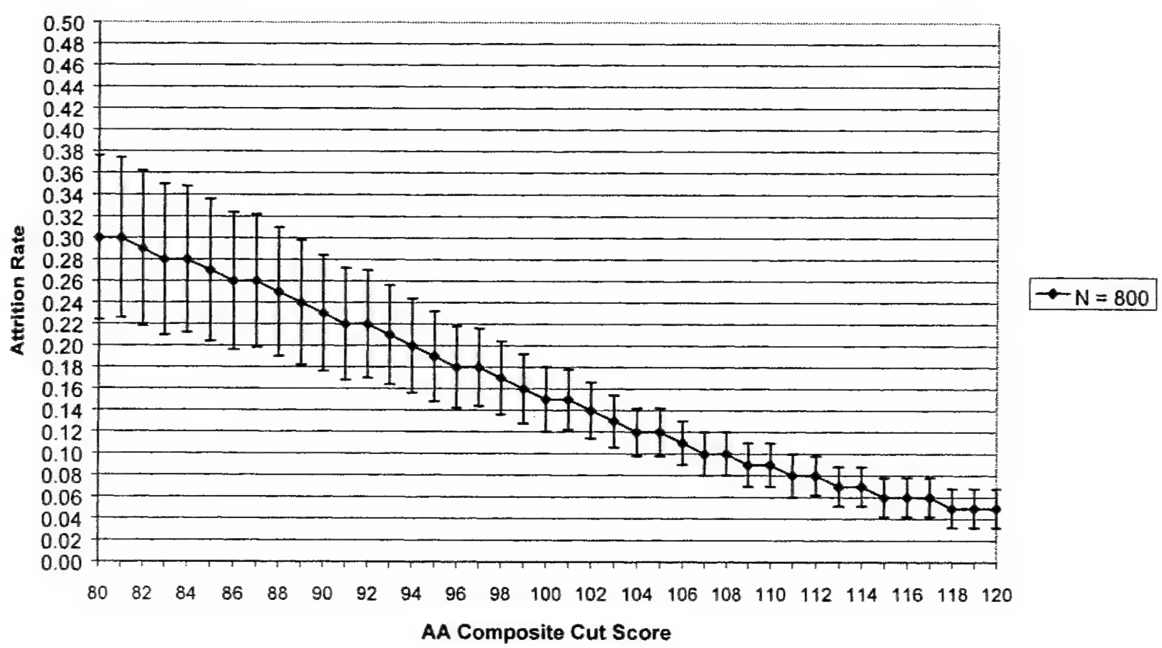


Figure 52. Attrition Rates with Standard Errors (SEs) by Cut Score for N=800



APPENDIX D: SAS PROGRAMS AND TECHNICAL DOCUMENTATION FOR SIMULATION

Overview and Steps for Running SAS Programs for Simulation

There are five SAS programs associated with running the simulation used in the current study. The names of these SAS programs, with a brief description of what each does, are as follows (hard copies of all programs appear on the proceeding pages):

- Run_Create_Table.sas. Main program for running the simulation. All other programs operate off of this program. This is where the configurations to run, location of other programs for running the simulation, plus location for outputting SAS datasets and tables, are specified.

- Create_Table.sas. Compiles estimated regression parameters and activates the other programs in the simulation to generate the Word table containing average attrition rates (and SEs) by sample size (*N*) and cut score.

- Simulate_Test_Score_Data_TwoAttempts.sas. Program for generating synthetic training performance and attrition data. Sample size (*N*) and number of samples to be replicated are based on configuration specifications.

- Estimate_Parameter.sas. Estimates regression parameters to be used as input for computing average attrition rates (and SEs) at varying cut scores and sample sizes (*N*).

- Tabulate_FailRates_FromNormal.sas. Estimates average attrition rate (and SE), then creates and outputs this information to Word table for each configuration.

Each program contains documentation on the procedures and computations performed by the program. To run the simulation, follow these steps:

1. On the computer's hard drive, create a folder (e.g., "SAS Simulation") to store the programs. Copy *all* programs to this folder. There are no constraints on the folder's name, as the programs are flexible enough to incorporate any name the user specifies.

2. Within the newly created folder add a subfolder (e.g., "Data"). This subfolder will contain the SAS datasets and tables outputted by the simulation. There are no constraints on the subfolder's name, as the programs are flexible enough to incorporate any name the user specifies.

3. Copy all configuration files representing the different conditions into the subfolder created in Step 2. Do *not* alter the names of configuration files, unless running a simulation different than the one conducted in the current study.

4. Start SAS. From the "Editor" window, go to File>Open. Locate the folder containing the SAS programs (created in Step 1), and select "Run_Create_Table.sas". When selected, hit "OK".

5. Follow the documentation contained in the program. At a minimum, users will need to specify the location (folder) containing the SAS programs (from Step 1) and the folder to which the SAS datasets and tables are to be outputted (from Step 2). Double-check that the location and names of these folders match those specified in the first two steps.

6. Run the program. To replicate the simulation, no other programs besides "Run_Create_Table.sas" need to be modified. All information required by other programs to successfully run the simulation is contained in the "Run_Create_Table.sas" program. *Do not make modifications to the other programs.*

Please note that replicating this simulation "as is", and for all conditions (in a single run), requires significant computer resources. Do not open other programs when the simulation is running. Users are advised to plan on running the simulation when computer resources, and the time it required to run it, can be dedicated (exclusively) to running the simulation.

Example of Configuration File (for Medium Difficulty, Medium Complexity Condition)

```
[SIMULATION CONFIGURATION]
Sample Size
5000
Simulation Repetitions
1
[TEST CONFIGURATION]
Number of Test
17
Minimum Passing Score
80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75 80.75
80.75 80.75 80.75
Test Score Validities
.29 .08 .37 .15 .32 .15 .17 .55 .24 .32 .26 .34 .02 .39 .29 .07 .24
Error Correlations
1.00 0.41 0.24 0.21 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.38 0.00 0.00 0.00 0.00
0.41 1.00 0.00 0.24 0.34 0.22 0.00 0.00 0.22 0.00 0.00 0.00 0.39 0.00 0.00 0.30 0.00
0.24 0.00 1.00 0.00 0.00 0.31 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.21 0.24 0.00 1.00 0.18 0.23 0.16 0.00 0.00 0.00 0.00 0.32 0.00 0.00 0.00 0.00 0.39
0.00 0.34 0.00 0.18 1.00 0.18 0.00 0.00 0.00 0.00 0.20 0.00 0.21 0.00 0.00 0.24 0.00
0.00 0.22 0.31 0.23 0.18 1.00 0.17 0.21 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.16 0.00 0.17 1.00 0.29 0.00 0.00 0.00 0.30 0.00 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 0.21 0.29 1.00 0.00 0.00 0.00 0.18 0.00 0.00 0.00 0.00 0.00
0.00 0.22 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.19 0.23 0.00 0.00 0.21 0.00 0.00
0.00 0.00 0.00 0.00 0.20 0.00 0.00 0.00 0.00 0.19 1.00 0.22 0.29 0.00 0.00 0.00 0.40
0.00 0.00 0.00 0.32 0.00 0.00 0.30 0.18 0.00 0.23 0.22 1.00 0.00 0.00 0.00 0.00 0.26
0.38 0.39 0.00 0.00 0.21 0.00 0.00 0.00 0.00 0.00 0.29 0.00 1.00 0.00 0.00 0.22 0.00
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.39
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.21 0.00 0.00 0.00 0.00 1.00 0.00 0.00
0.00 0.30 0.00 0.00 0.24 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.22 0.00 0.00 1.00 0.00
0.00 0.00 0.00 0.39 0.00 0.00 0.00 0.00 0.00 0.00 0.40 0.26 0.00 0.39 0.00 0.00 1.00
Number of X
1
Mean of X
118
Variance of X
81

Regression Weights
63.56 86.83 62.56 82.93 74.32 80.10 75.46 39.49 68.84 63.04 60.04 68.74 85.61 69.99
62.45 86.41 79.77
.24 .06 .24 .10 .18 .11 .11 .43 .17 .23 .25 .18 .02 .22 .24 .03 .13
Test Score Variances
56.59 46.73 33.03 38.71 24.31 39.04 33.98 49.15 40.34 41.64 74.09 25.77 74.13 25.77
56.31 21.68 21.65
Simulation Random Number Seed
1001
[REFERENCE POPULATION]
Number of X
1
Mean of X
100
Variance of X
400
Alternative Cut Score Range: LOW, HIGH, STEPSIZE
80 120 1
```

****

Example of Configuration File (for Medium Difficulty, Medium Complexity Condition)

```
FILENAME: AvgDiff_MedR.Param.txt

DESCRIPTION: Test score parameters for MOS XX with "problem" data points (e.g.,
recruits below cut score, plus outlier on TestXX) excluded from parameter estimation.

NOTE: Error structure does not include negatively correlated errors.

(1) Training Difficulty
    *Y-intercepts are empirical estimates meant to reflect MOS "average" in training
    difficulty (12-13% attrit rate).
(2) Test Validities
    *Test validities average to .25 ("average") to reflect medium complexity MOS.

*******************************************************************************
```

Program A: Run_Create_Table.sas

```
*******************************************************************************
FILENAME: Run_Create_Table.sas
*******************************************************************************;

*******************************************************************************
DESCRIPTION:

This program creates a table with MEAN and STANDARD ERROR estimates of
expected attrition/failure rates at alternative cut scores for specified
sample sizes.

* ROW = Cut Scores
* COLUMN = Sample Size
* CELL = MEAN & STANDARD ERROR

NOTE:
(1) Table configuration is specified in the input text file.
(2) Parameter estimates are stored separately by sample size and replication.
*******************************************************************************;

*******************************************************************************
STEP 1: SET GENERAL PARAMETERS
* mDataDir specifies location of directory containing parameter configuration
  files and to which SAS datasets, output & log files, and tables are outputted.
* SET mDropTest=YES to drop Test Score and only keep ATTRIT. Else, set to NO.
*******************************************************************************;
%let mDataDir=D:\SAS Simulation\Data;
%let mDropTest=YES;

*******************************************************************************
STEP 2: SET PROGRAMS DIRECTORY LOCATION
* mProgDir specifies location of directory containing SAS programs.
*******************************************************************************;
%let mProgDir=D:\SAS Simulation;

*******************************************************************************
STEP 3: SET TITLE OF OUTPUT TABLE (OPTIONAL).
*******************************************************************************;
%let titleline1 "This is title line #1";
%let titleline2 "This is title line #2";
%let titleline3 "This is title line #3";

*******************************************************************************
STEP 4: RUN PROGRAM
* mDataFile specifies name of all configuration files, SAS datasets, and RTF
  files read by and outputted by the simulation. NOTE: This name reflects key
  configuration parameters (i.e., level of difficulty and complexity).
*******************************************************************************;
options formchar='|-++++++' nodate nonumber mprint;

/**Medium Difficulty, Medium Complexity Condition**/
%let mDataFile=AvgDiff_MedR;
%include "&mProgDir\Create_Table.sas";

/**Medium Difficulty, High Complexity Condition**/
%let mDataFile=AvgDiff_HighR;
%include "&mProgDir\Create_Table.sas";
```

Program A: Run_Create_Table.sas

```
/**Medium Difficulty, Low Complexity Condition**/
%let mDataFile=AvgDiff_LowR;
%include "&mProgDir\Create_Table.sas";

/**Low Difficulty, Medium Complexity Condition**/
%let mDataFile=LowDiff_MedR;
%include "&mProgDir\Create_Table.sas";

/**Low Difficulty, High Complexity Condition**/
%let mDataFile=LowDiff_HighR;
%include "&mProgDir\Create_Table.sas";

/**Low Difficulty, Low Complexity Condition**/
%let mDataFile=LowDiff_LowR;
%include "&mProgDir\Create_Table.sas";

/**High Difficulty, Medium Complexity Condition**/
%let mDataFile=HighDiff_MedR;
%include "&mProgDir\Create_Table.sas";

/**High Difficulty, High Complexity Condition**/
%let mDataFile=HighDiff_HighR;
%include "&mProgDir\Create_Table.sas";

/**High Difficulty, Low Complexity Condition**/
%let mDataFile=HighDiff_LowR;
%include "&mProgDir\Create_Table.sas";
```

Program B: Create_Table.sas

```
*****************************************************************************
FILENAME: Create_Table.sas
*****************************************************************************;

*****************************************************************************
DESCRIPTION: Compiles estimated regression parameters and activates other
programs (e.g., Simulate_Test_Score_Data_TwoAttempts.sas, Estimate_Parameter.sas)
for generating Word table reporting the estimated average attrition rate (and
standard error) by cut score and sample size.
NOTE: Run this program through RUN_CREATE_TABLE.SAS. Do NOT modify this program.
*****************************************************************************;

*****************************************************************************
* mColFile specifies name of SAS dataset containing logistic regression
  parameters by sample size across replications. NOTE: Name of file reflects
  mDataFile specification from Run_Create_Table.sas.
* mOutFile specifies name of SAS dataset containing attrition rates by cut scores
  across replications. NOTE: This file is written in mDataDir directory. Name of
  file reflects mDataFile specification from Run_Create_Table.sas.
* mRtfFile specifies name of the RTF file version of the OUTPUT TABLE. This file
  can be imported directly to MS Word. NOTE: This file is written in mDataDir
  directory. Name of file reflects mDataFile specification from
  Run_Create_Table.sas.
*****************************************************************************;
%let mColFile=&mDataFile._LogistParam;
%let mOutFile=&mDataFile._Table;
%let mRtfFile=&mDataFile..rtf;
proc printto print="&mDataDir\&mDataFile._Output.txt"
log="&mDataDir\&mDataFile..log";run;

*****************************************************************************
(1) Reads in parameters from configuration file.
*****************************************************************************;
data _null_;
  file print;
  length strTmp $ 100;
  infile "&mDataDir.\&mDataFile..Param.txt" lrecl=100 TRUNCOVER;
  do until (trim(strTmp)="[SIMULATION CONFIGURATION]");
    input strTmp $100.;
      put strTmp;
  end;

  nNumSize = 0;
  input strTmp $100.;
  do i=1 to 10 until(nSize=.);
    input nSize @;
    put "NSIZE = " nSize;
      nNumSize = nNumSize + 1;
    if (nSize^=.) then
      call symput(compress("mSize"||put(i,2.)),left(put(nSize,5.)));
  end;
  nNumSize = nNumSize - 1;
  put "Number of Sample Sizes = " nNumSize;
  call symput("mNumSize",put(nNumSize,2.));

  input / strTmp $100.;
  input nReps;
```

```
  put "NREPS = " nReps;
  call symput("mNumRep",put(nReps,5.));

  stop;
run;

%macro MacroCreateTable;

********************************************************************************
(2) Creates the simulated test score data.
********************************************************************************;
  %do iSize = 1 %to &mNumSize;
    %let mNumSSN = &&mSize&iSize;
    %include "&mProgDir\Simulate_Test_Score_Data_TwoAttempts.sas";
  %end;

********************************************************************************
(3) Computes the parameter estimates across replications.
********************************************************************************;
  %include "&mProgDir\Estimate_Parameter.sas";

********************************************************************************
(4) Generates the attrition table.
********************************************************************************;
  %include "&mProgDir\Tabulate_FailRates_FromNormal.sas";

%mend;
%MacroCreateTable;

********************************************************************************
*
END OF PROGRAM.
********************************************************************************;
```

Program C: Simulate_Test_Score_Data_TwoAttempts.sas

```
*****************************************************************************
FILENAME: Simulate_Test_Score_Data_TwoAttempts.sas
*****************************************************************************;

*****************************************************************************
DESCRIPTION: Program for generating synthetic training performance and attrition
data.
NOTE: Run this program through RUN_CREATE_TABLE.SAS. Do NOT modify this program.
*****************************************************************************;

libname DataDir "&mDataDir";
filename ParFile "&mDataDir\&mDataFile..Param.Txt";

proc iml;

*****************************************************************************
READING IN TEST CONFIGURATION INFORMATION FROM INPUT PARAMETER FILE.
  * macro variable = &mParFile

(1) Test score data dimension.
    * nNumTest - scalar number of tests
    * nNumSSN  - scalar number of SSNs (Sample Size)
    * nNumRep - scalar number of simulation repetitions
(2) Minimum passing scores for school tests, which can vary across tests.
    * fMinPassScore - vector of nNumberTest elements
(3) "Restricted" test validities.
    * fRxy - vector of nNumberTest validities. Equals corr(X,Y[1:nNumberTest])
(4) Intra-person test score "error" correlations. Allow unequal correlations.
    * fRho - symmetric matrix. nNumberTest*nNumberTest intra-person error
correlations.
(5) Mean and variance of predictor matrix X.
    * nNumX - scalar number of predictors, including constant
    * fMuX - test score means
    * fVarX - test score variances
(5) Regression constants and coefficients for test score means conditional on X.
    * fBeta - (p+1) by (nNumberTest) matrix. Columns represent tests. Note that
              E{Y[j]|Xvec} = t(Xvec)*fBeta[,j]
(6) Variance of tests (restricted to MOS school sample)
    * fVarY - 1 X nNumTest vector of test variances
*****************************************************************************;
  infile ParFile;

  nNumSSN = &mNumSSN;
  print nNumSSN[label="Sample Size"];
  nNumRep = &mNumRep;
  print nNumRep[label="Number of Repetitions"];

  do until (trim(strLabel)="[TEST CONFIGURATION]");
    input strLabel $RECORD.;
  end;

  input strLabel $RECORD. / nNumTest;
  print nNumTest[label=strLabel];

  input strLabel $RECORD.;
  fMinPassScore = repeat(0,1,nNumTest);
  do j=1 to nNumTest;
```

```
    input tmpVal @;
      fMinPassScore[j] = tmpVal;
  end;
  print fMinPassScore[label=strLabel];

  input;
  input strLabel $RECORD.;
  fRxy = repeat(0,1,nNumTest);
  do j=1 to nNumTest;
    input tmpVal @;
      fRxy[j] = tmpVal;
  end;
  print fRxy[label=strLabel];

  input;
  input strLabel $RECORD.;
  fRho = repeat(0,nNumTest,nNumTest);
  do i=1 to nNumTest;
    do j=1 to nNumTest;
      input tmpVal @;
        fRho[i,j] = tmpVal;
    end;
      input;
  end;
  print fRho[label=strLabel];

  input strLabel $RECORD. / nNumX;
  print nNumX[label=strLabel];

  input strLabel $RECORD.;
  fMuX = repeat(0,1,nNumX);
  do j=1 to nNumX;
    input tmpVal @;
      fMuX[j] = tmpVal;
  end;
  print fMuX[label=strLabel];

  input;
  input strLabel $RECORD.;
  fVarX = repeat(0,nNumX,nNumX);
  do i=1 to nNumX;
    do j=1 to nNumX;
      input tmpVal @;
        fVarX[i,j] = tmpVal;
    end;
      input;
  end;
  print fVarX[label=strLabel];

  input strLabel $RECORD.;
  fBeta = repeat(0,nNumX+1,nNumTest);
  do i=1 to nNumX+1;
    do j=1 to nNumTest;
      input tmpVal @;
        fBeta[i,j] = tmpVal;
    end;
      input;
```

```
   end;
   print fBeta[label=strLabel];

   input strLabel $RECORD.;
   fVarY = repeat(0,1,nNumTest);
   do j=1 to nNumTest;
     input tmpVal @;
       fVarY[j] = tmpVal;
   end;
   print fVarY[label=strLabel];

   input / strLabel $RECORD. / nRandSeed;
   print nRandSeed[label=strLabel];

********************************************************************************
CREATING OUTPUT FILE FOR SYNTHETIC TRAINING PERFORMANCE AND ATTRITION DATA.
  * FILEREF = DataDir.DataFile
********************************************************************************;
strColNames = compress(concat("X",char(0:nNumX)));
if ("&mDropTest"^="YES") then do;
  strColNames = strColNames||compress(concat("SCORE1_",char(1:nNumTest)));
  strColNames = strColNames||compress(concat("SCORE2_",char(1:nNumTest)));
end;
strColNames = strColNames||"ATTRIT";
create DataDir.&mDataFile._N&mNumSSN var ("REP"||strColNames);

********************************************************************************
GENERATING SYNTHETIC DATA THAT REFLECTS CONFIGURATION PARAMETERS (e.g., MEAN,
VARIANCE, etc.)
********************************************************************************;

/* Cholesky of variance of X */
rootVarX = root(fVarX);
/* "n X 1" unit vector */
oneXVec = repeat(1,nNumSSN,1);

/* Root of error variances */
mseScore = ((1-fRxy##2)#fVarY)##.5;
/* Error covariance */
errorVar = diag(mseScore)*fRho*diag(mseScore);
/* Cholesky of error covariance */
rootVarError = root(errorVar);

do iRep=1 to nNumRep;
   /* Simulating training performance over two attempts */

   /* Simulating samples of AA composite scores of N size (i.e., nNumSSN) with
   mean and variance approximately equal to mean and variance of real-world data.
   */
   fXmat  = oneXVec || oneXVec*fMuX + rannor(repeat(1,nNumSSN,nNumX))*rootVarx;

   /* Test1 and Test2 are samples of simulated test scores with mean, variance,
   validities, etc., approximately equal to real-world estimates. */
   fTest1 = fXmat*fBeta +
rannor(repeat(nRandSeed,nNumSSN,nNumTest))*rootVarError;
   fTest2 = fXmat*fBeta +
rannor(repeat(nRandSeed,nNumSSN,nNumTest))*rootVarError;
```

Program C: Simulate_Test_Score_Data_TwoAttempts.sas

```
     /* Identifying max test score across two attempts to compute attrition */
     fTestMax = fTest1<>fTest2;

   /* If mDropTest set to "Yes", dropping test score data, but keeping attrition
   data to minimize file size. Otherwise, all data (test scores, attrition)
   outputted to SAS dataset. */
   if ("&mDropTest"^="YES") then do;
    OUTMAT = repeat(iRep,nNumSSN,1)||
             fXmat   ||
                 fTest1 ||
                 fTest2 ||
             /* Computing attrition (1="ATTRIT", 0="NO ATTRIT") based on max test
             score and minimum passing scores */
                 (fTestMax < oneXVec*fMinPassScore)[,<>];
   end;
   else do;
    OUTMAT = repeat(iRep,nNumSSN,1)||
             fXmat   ||
             /* Computing attrition (1="ATTRIT", 0="NO ATTRIT") based on max test
             score and minimum passing scores */
             (fTestMax < oneXVec*fMinPassScore)[,<>];
   end;

   append from OUTMAT;

 end;

 close DataDir.&mDataFile._N&mNumSSN;

 quit;
 run;

 ********************************************************************************
 END OF PROGRAM.
 ********************************************************************************;
```

Program D: Estimate_Parameter.sas

```
*******************************************************************************
FILENAME: Estimate_Parameter.sas
*******************************************************************************;

*******************************************************************************
DESCRIPTION: Program for estimating regression parameters, which become input
for estimating average attrition rates and standard errors by sample size and
cut score.
NOTE: Run this program through RUN_CREATE_TABLE.SAS. Do NOT modify this program.
*******************************************************************************;

/* Macro for compiling individual SAS datasets containing synthetic data for a
given sample size (across X replications). */
%macro SetFiles;
  %do iSize = 1 %to &mNumSize;
    DataDir.&mDataFile._N&&mSize&iSize (in=In&&mSize&iSize)
  %end;
%mend;

/* Macro for computing sample sizes to be included in TestScoreData. */
%macro NSizes;
  In&mSize1*&mSize1
  %do iSize = 2 %to &mNumSize;
     + In&&mSize&iSize*&&mSize&iSize
  %end;
%mend;

/* Merging individual SAS datasets containing synthetic data for a given sample
size (across X replications) into single, omnibus dataset with variable NSIZE. */
data TestScoreData /view=TestScoreData;
  length NSIZE 4;
  set %SetFiles;
  NSIZE = %NSizes;
run;

/* Estimating regression parameters for each replication (REP) by sample size
(NSIZE). Outputting parameters to specified SAS dataset. */
proc logistic data=TestScoreData
  outest=datadir.&mColFile (keep=NSIZE REP Intercept X1)
  descending noprint;
  model attrit = x1;
  by NSIZE rep;
quit;
run;

*******************************************************************************
END OF PROGRAM.
*******************************************************************************;
```

Program E: Tabulate_FailRates_FromNormal.sas

```
*********************************************************************************
FILENAME: Tabulate_FailRates_FromNormal.sas
*********************************************************************************;

*********************************************************************************
DESCRIPTION: Estimates average attrition rate (and standard error) by sample size
and cut score, then creates table and outputs this information to RTF file.
NOTE: Run this program through RUN_CREATE_TABLE.SAS. Do NOT modify this program.
*********************************************************************************;

libname DataDir "&mDataDir";
filename RowFile "&mDataDir\&mDataFile..Param.Txt";

proc iml;

*********************************************************************************
**
READING IN POPULATION PARAMETERS AND CUT SCORE RANGE FOR ESTIMATING ATTRITION
RATES.
 * macro variable = &mRowFile

(1) Mean and variance of predictor matrix X in REFERENCE POPULATION.
    * nNumX - scalar number of predictors, including constant.
    * fMuX - reference population mean for AA composite.
    * fVarX - reference population variance for AA composite.
(2) Alternative Cut Scores along the row dimension.
    * nNumCut - total number of cut scores.
    * fXCut - list of cut scores for which attrition rates (and SEs) will be
      estimated.
*********************************************************************************
*;
  infile RowFile;

  do until (trim(strLabel)="[REFERENCE POPULATION]");
    input strLabel $RECORD.;
  end;

  input strLabel $RECORD. / nNumX;
  print nNumX[label=strLabel];

/* Reading in reference population mean. */
  input strLabel $RECORD.;
  fMuX = repeat(0,1,nNumX);
  do j=1 to nNumX;
    input tmpVal @;
      fMuX[j] = tmpVal;
  end;
  print fMuX[label=strLabel];

/* Reading in reference population variance.*/
  input;
  input strLabel $RECORD.;
  fVarX = repeat(0,nNumX,nNumX);
  do i=1 to nNumX;
    do j=1 to nNumX;
      input tmpVal @;
        fVarX[i,j] = tmpVal;
```

```
      end;
      input;
    end;
    print fVarX[label=strLabel];

 /* Reading in specified cut score range. */
    input strLabel $RECORD.;
    input fCutLO fCutHI fCutSTEP;
    print fCutLO fCutHI fCutSTEP;
    nNumCut = floor((fCutHI-fCutLO)/fCutSTEP) + 1;
    print nNumCut[label="Number of Cut Scores"];
    fXCut = repeat(0,1,nNumCut);
    do j=1 to nNumCut;
        fXCut[j] = fCutLO + (j-1)*fCutSTEP;
    end;
    print fXCut[label=strLabel];

 /* Copy LO, HI, STEP to macro variables for later processing. */
    call symput("mCutLO",compress(char(fCutLO)));
    call symput("mCutHI",compress(char(fCutHI)));
    call symput("mCutSTEP",compress(char(fCutSTEP)));

*******************************************************************************
CREATING OUTPUT DATASET CONTAINING ESTIMATED ATTRITION RATES BY SAMPLE SIZE AND
CUT SCORE.
  * FILEREF = DataDir.&mOutFile;
*******************************************************************************;

    strColNames = compress(concat("PATTRIT",char(fXCut)));
    create DataDir.&mOutFile var ({"NSIZE" "REP"} || strColNames);

*******************************************************************************
ESTIMATING ATTRITION RATES BY SAMPLE SIZE AND CUT SCORE.
  * FILEREF = DataDir.&mColFile;
*******************************************************************************;

    nNumQuant = 5000;
    /* Generating quantiles based on reference population mean and variance */
    quantX = probit((1:(nNumQuant-1))/nNumQuant)*sqrt(fVarX[1,1]) + fMuX;
    /* Creating nNumQuant BY nNumCut matrix of 0 and 1 to denote pass cut score */
    aboveCut = repeat(t(quantX),1,ncol(fXcut)) > repeat(fXcut,ncol(quantX),1);

    strBetaNames = "Intercept" || compress(concat("X",char(1:nNumX)));

    use DataDir.&mColFile;

 /* Looping through sample size and replications */
    do data;
      read next var {"NSIZE" "REP"};
      read current var (strBetaNames) into fBeta;

        /* Estimating probability that recruits within a quantile would not
        complete training */
        quantProbAttrit = 1/(1 + exp(-fBeta[1] - quantX*fBeta[2]));

        /* Calculating attrition rate for each alternative cut score in specified
        range. For given alternative cut score, the attrition rate is the simple
```

```
      arithmetic average of probabilities of not completing (i.e.,
      quantProbAttrit) associated with AA quantiles above the cut score. This is
      equivalent to average of probability of not completing weighted by density
      of AA. */
    cutProbAttrit = NSIZE || REP || (quantProbAttrit*aboveCut)/aboveCut[+,];

      append from cutProbAttrit;
  end;

  close DataDir.&mColFile;

quit;
run;

*********************************************************************************
CREATING AND OUTPUTTING RTF FILE CONTAINING TABLE WITH ESTIMATED ATTRITION
RATES BY SAMPLE SIZE AND CUT SCORE.
 * FILEREF = DataDir.&mOutFile AND &mDataDir\&mRtfFile;
*********************************************************************************;

/* Macro for creating sample size labels for table. */
%macro SizeLabel;
  %do iSize=1 %to &mNumSize;
    &&mSize&iSize="N = &&mSize&iSize"
  %end;
%mend;

/* Macro for creating cut score variables needed to build table. */
%macro CutScoreVars;
  %do i=&mCutLO %to &mCutHI %by &mCutSTEP;
    PATTRIT&i
  %end;
%mend;

/* Macro for creating cut score labels for table. */
%macro CutScoreLabel;
  %do i=&mCutLO %to 100 %by &mCutSTEP;
    PATTRIT&i = "GM= &i"
  %end;
  %do i=100 %to &mCutHI %by &mCutSTEP;
    PATTRIT&i = "GM=&i"
  %end;
%mend;

proc format;
  value nsizefmt %SizeLabel;
run;

/* Creating and outputting table containing average (AVG) attrition rates and
standard errors (STD) by sample size and cut score. */
ods rtf file="&mDataDir\&mRtfFile";
proc tabulate data=DataDir.&mOutFile;
  title1 &titleline1;
  title2 &titleline2;
  title3 &titleline3;
  class NSIZE;
  format NSIZE nsizefmt.;
```

```
   var %CutScoreVars;
   table %CutScoreVars,
         NSIZE*(MEAN*F=6.2 STD*F=6.3)
         /box="Cut Scores" rts=20;
   keylabel mean="AVG"
            std ="STD";
   label NSIZE="Alternative Sample Sizes"
         %CutScoreLabel;
run;
ods rtf close;

*********************************************************************************
END OF PROGRAM.
*********************************************************************************;
```

APPENDIX E: SAS PROGRAMS AND TECHNICAL DOCUMENTATION FOR PERFORMING ATTRITION RATES ANALYSIS

Overview and Steps for Running SAS Programs for Attrition Rates Analysis

Only a single SAS program is needed to perform an attrition rates analysis, Tabulate_Attrit Rates_ForSchool.sas (a hard copy of this program appears on the proceeding pages). The program contains documentation on the procedures and computations performed by the program, plus the specifications users need to make in order to run it. The program was designed to minimize the number of specifications users must make in order to run the program. Users can easily customize these specifications to fit their analysis needs. In general, to run an attrition rates analysis, follow these steps:

1. On the computer's hard drive, create a folder (e.g., "SAS Simulation"). This folder will contain the SAS program, and all datasets and tables outputted by the program. There are no constraints on the folder's name, as the program is flexible enough to incorporate any name the user specifies.

2. Copy the program (Tabulate_Attrit Rates_ForSchool.sas) and the SAS dataset containing the MOS school data to be analyzed to this folder. Prior to running the analyses, be sure that the integrity of the MOS school data has been verified; suggestions for doing so were made in the "Discussion" section of this report. At a minimum check the integrity of AA composite scores and attrition data, as the attrition rates analysis primarily utilizes these data. Note, that the variable containing attrition data should be a dichotomous, numeric variable (e.g., 1="attrit", 0="no attrit"), with non-academic attritions classified as "missing." It is important that all non-academic attritions are excluded from the analysis.

3. Start SAS. From the "Editor" window, go to File>Open. Locate the folder created in Step 1, and select "Tabulate_Attrit Rates_ForSchool.sas." When file has been selected, click "OK".

4. Follow the documentation contained in the program. At a minimum, users will need to specify:

    - The location (folder) containing the SAS program and dataset with MOS school data (created in Step 1);

    - The name of the SAS dataset containing the MOS school data to be analyzed;

    - The variables names (in the SAS dataset) for the AA composite and attrition data;

    - The mean and variance of the AA composite (applicable to the MOS to be analyzed) for the appropriate reference population; and

    - The range of cut scores for which attrition rates should be estimated.

5. After the above have been specified (and any additional options, such as titles for the table), run the program. All information required to successfully perform the attrition rates analysis is contained at the top of the "Tabulate_Attrit Rates_ForSchool.sas" program. *Users do not need to make modifications to the rest of the program.*

The table outputted by the program is comparable to the table produced by the simulation, except the table is composed of only two columns. The first column ("Cut Scores") lists the range of alternative cut scores, as specified by the user. The second column ("Attrit") reports the corresponding estimated attrition rates. An example table appears after the copy of the program. The program outputs the table to an .RTF file that can be easily opened in MS Word.

Tabulate_AttritRates_ForSchool.sas

```
******************************************************************************
FILENAME: Tabulate_AttritRates_ForSchool.sas
******************************************************************************;

******************************************************************************
DESCRIPTION: Program for estimating attrition rates by cut score using available
MOS school data.
******************************************************************************;

******************************************************************************
STEP 1A: SET FILE LOCATIONS.
The following parameters are required. They must be modified in order to run the
program successfully.
* mDataDir specifies location of directory containing SAS datasets,
  configuration files, etc., used by program, and to which all SAS datasets and
  tables generated by program are outputted.
* mDataFile specifies name of SAS dataset containing MOS school data. NOTE: By
  default, name of dataset becomes first part of filename for all files
  generated by the program. SEE mColFile, mOutFile, and mRtfFile.
******************************************************************************;
%let mDataDir=D:\SAS Simulation\Data;
%let mDataFile=MOS55d;

******************************************************************************
STEP 1B: SET FILE LOCATIONS (con.)
NOTE: The following parameters are optional. They do not have to be modified
unless desired by the user.
* mColFile specifies name of SAS dataset containing logistic regression
  parameters. NOTE: The default filename is mDataFile + "._LogistParam".
* mOutFile specifies name of SAS dataset containing attrition rates by cut
  scores. The file becomes input to the Word table produced by this program.
  NOTE: The default filename is mDataFile + "._Table".
* mRtfFile specifies name of the RTF file version of the table containing
  estimated attrition rates by cut score. This file can be imported opened in
  Word. NOTE: The default filename is mDataFile + ".rtf".
******************************************************************************;
%let mColFile=&mDataFile._LogistParam;
%let mOutFile=&mDataFile._Table;
%let mRtfFile=&mDataFile..rtf;

******************************************************************************
STEP 2: SPECIFY VARIABLE NAMES IN SCHOOL DATASET.
* mAAComp specifies the variable name of the AA composite (e.g., AR, GM, MK, AS,
  etc.) used to determine enlistment eligibility. NOTE: This information will
  also be used to label cut scores in the outputted table (e.g., GM=80, GM=82,
  GM=84, etc.).
* mAttrit specifies the variable name containing academic attrition information.
******************************************************************************;
%let mAAComp=GM;
%let mAttrit=attrit;

******************************************************************************
STEP 3: SET REFERENCE POPULATION PARAMETERS AND CUT SCORE RANGE.
* fMuX specifies the reference population mean for the AA composite.
* fVarX specifies the reference population variance for the AA composite.
* fCutLO defines the lower bound of the range of cut scores for which attrition
  rates will be estimated.
```

```
  * fCutHI defines the upper bound of the range of cut scores for which attrition
    rates will be estimated.
  * fCutSTEP specifies which cut scores within the defined range of cut scores
    (see fCutLO and fCutHI) attrition rates will be estimated for (and will appear
    in the outputted table). The value specified here defines the increment in the
    cut score range.
****************************************************************************;
%let fMuX=100;
%let fVarX=400;
%let fCutLO=80;
%let fCutHI=120;
%let fCutSTEP=1;

****************************************************************************
STEP 4: SET TITLE OF OUTPUT TABLE (OPTIONAL).
****************************************************************************;
%let titleline1 "This is title line #1";
%let titleline2 "This is title line #2";
%let titleline3 "This is title line #3";


****************************************************************************
START OF PROGRAM. DO NOT MODIFY SAS CODE BEYOND THIS POINT.
****************************************************************************;

libname DataDir "&mDataDir";


****************************************************************************
COMPUTING REGRESSION PARAMETERS TO ESTIMATE ATTRITION RATES AT DIFFERENT AA
COMPOSITE CUT SCORES.
  * FILEREF = DataDir.&mDataFile AND Datadir.&mColFile;
****************************************************************************;

proc logistic data=DataDir.&mDataFile
  outest=Datadir.&mColFile (keep= Intercept &mAAComp)
  descending noprint;
  model &mAttrit = &mAAComp;
quit;
run;

****************************************************************************
READING IN POPULATION PARAMETERS AND CUT SCORE RANGE FOR ESTIMATING ATTRITION
RATES.
****************************************************************************;

proc iml;

/* Reading in reference population parameters and cut score range from macro
above. */
  fMuX=&fMuX;
  fVarX=&fVarX;
  fCutLO=&fCutLO;
  fCutHI=&fCutHI;
  fCutSTEP=&fCutSTEP;

  print fMuX[label="Population Mean of AA Composite"];
```

```
  print fVarX[label="Population Variance of AA Composite"];
  print fCutLO fCutHI fCutSTEP;

  nNumCut = floor((fCutHI-fCutLO)/fCutSTEP) + 1;
  print nNumCut[label="Number of Cut Scores"];
  fXCut = repeat(0,1,nNumCut);
  do j=1 to nNumCut;
      fXCut[j] = fCutLO + (j-1)*fCutSTEP;
  end;
  print fXCut[label="Alternative Cut Scores"];

/* Copy LO, HI, STEP to macro variables for later processing. */
  call symput("mCutLO",compress(char(fCutLO)));
  call symput("mCutHI",compress(char(fCutHI)));
  call symput("mCutSTEP",compress(char(fCutSTEP)));

*******************************************************************************
CREATING OUTPUT DATASET CONTAINING ESTIMATED ATTRITION RATES BY CUT SCORE.
  * FILEREF = DataDir.&mOutFile;
*******************************************************************************;
  strColNames = compress(concat("PATTRIT",char(fXCut)));
  create DataDir.&mOutFile var (strColNames);

*******************************************************************************
ESTIMATING ATTRITION RATES BY CUT SCORE
  * FILEREF = DataDir.&mColFile;
*******************************************************************************;
  nNumQuant = 5000;
  /* Generating quantiles based on reference population mean and variance */
  quantX = probit((1:(nNumQuant-1))/nNumQuant)*sqrt(fVarX[1,1]) + fMuX;
  /* Creating nNumQuant BY nNumCut matrix of 0 and 1 to denote pass cut score */
  aboveCut = repeat(t(quantX),1,ncol(fXcut)) > repeat(fXcut,ncol(quantX),1);

  strBetaNames = "Intercept" || "&mAAComp";

  use DataDir.&mColFile;
      read var (strBetaNames) into fBeta;

      /* Estimating probability that recruits within a quantile would not
      complete training */
      quantProbAttrit = 1/(1 + exp(-fBeta[1] - quantX*fBeta[2]));

      /* Calculating attrition rate for each alternative cut score in specified
      range. For given alternative cut score, the attrition rate is the simple
      arithmetic average of probabilities of not completing (i.e.,
      quantProbAttrit) associated with AA quantiles above the cut score. This is
      equivalent to average of probability of not completing weighted by density
      of AA.*/
      cutProbAttrit = (quantProbAttrit*aboveCut)/aboveCut[+,];

      append from cutProbAttrit;

   close DataDir.&mColFile;

quit;
run;
```

Tabulate_AttritRates_ForSchool.sas

```
*********************************************************************************
CREATING AND OUTPUTTING RTF FILE CONTAINING TABLE WITH ESTIMATED ATTRITION RATES
BY CUT SCORE.
 * FILEREF = DataDir.&mOutFile AND &mDataDir\&mRtfFile;
*********************************************************************************;

/* Macro for creating cut score variables needed to build table. */
%macro CutScoreVars;
  %do i=&mCutLO %to &mCutHI %by &mCutSTEP;
    PATTRIT&i
  %end;
%mend;

/* Macro for creating cut score labels for table. */
%macro CutScoreLabel;
  %do i=&mCutLO %to 100 %by &mCutSTEP;
    PATTRIT&i = "&mAAComp= &i"
  %end;
  %do i=100 %to &mCutHI %by &mCutSTEP;
    PATTRIT&i = "&mAAComp=&i"
  %end;
%mend;

/* Creating and outputting table containing estimated attrition rates by cut
score. */
ods rtf file="&mDataDir\&mRtfFile";
proc tabulate data=DataDir.&mOutFile;
  title1 &titleline1;
  title2 &titleline2;
  title3 &titleline3;
  var %CutScoreVars;
  table %CutScoreVars,
        MEAN*F=6.2
        /box="Cut Scores" rts=20;
  keylabel mean="Attrit";
  label %CutScoreLabel;
run;
ods rtf close;

*********************************************************************************
END OF PROGRAM.
*********************************************************************************;
```

Example of Table Produced by Attrition Rates Analysis

Table 1. Estimated Attrition Rates by Cut Score for MOS XX (N=XXX)

Cut Scores	Attrit
GM= 85	0.27
GM= 86	0.26
GM= 87	0.25
GM= 88	0.25
GM= 89	0.24
GM= 90	0.23
GM= 91	0.22
GM= 92	0.21
GM= 93	0.21
GM= 94	0.20
GM= 95	0.19
GM= 96	0.18
GM= 97	0.18
GM= 98	0.17
GM= 99	0.16
GM=100	0.15
GM=101	0.15
GM=102	0.14
GM=103	0.13
GM=104	0.13
GM=105	0.12